

# Measuring Downward Nominal and Real Wage Rigidity - Why Methods Matter\*

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## Abstract

Downward wage rigidity may enhance job destruction in periods of decreasing demand. But although wage rigidity is an important topic, there is no full consensus in the literature on how to measure downward nominal and real wage rigidity. We conceptually and empirically compare the three commonly used methods for estimating wage rigidity: the simple IWFP approach, the model based IWFP approach and the Maximum Likelihood approach. We estimate the three models on administrative panel data (Dutch administrative data at the individual level for the years 2006-2012). One main finding is that assumptions regarding the 'notional' wage change distribution (which would prevail in the absence of wage rigidity) are an important determinant of the level of wage rigidity measured. We argue that the model-based IWFP approach, we conclude that the model-based IWFP approach is the preferred model of the three, for it has the most sophisticated method to address measurement error and the assumptions regarding the wage change distribution that would prevail in absence of wage rigidity are most plausible.

Furthermore we have researched the correlation between wage rigidity and worker and firm characteristics. Although the methods do not agree on the amount of rigidity, they agree for a large part on what variables have a positive or negative relation with downward nominal or real wage rigidity. We find that the presence of wage rigidity is unevenly distributed among groups of workers: downward nominal and real wage rigidity in the Netherlands are positively related to a higher age, higher education, open-end contracts, full-time contracts and to working in a firm that experiences zero or positive employment growth. The consistency in the findings regarding the determinants of wage rigidity indicate that all three methods measure the same phenomenon, which implies that estimates of determinants of wage rigidity can be compared over countries using any of the three methods. However, for measuring the fraction of workers covered by downward nominal or real wage rigidity, the choice of the method matters.

Besides, we contribute to the literature by providing accurate, internationally comparable estimates of wage rigidity in the Netherlands. The overall picture is that the Netherlands has a less than average amount of downward nominal wage rigidity but an above average level of downward real wage rigidity, compared internationally. Downward real wage rigidity is higher in Belgium (known for its inflation compensation), France and Sweden, while Denmark, Italy, Germany, the UK and the US show a substantially lower downward real wage rigidity.

**Keywords:** Wage Rigidity, Wage Change Distribution, Wage Flexibility, Downward Nominal Wage Rigidity, Downward Real Wage Rigidity

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# 1 Introduction

Downward wage rigidity is an important topic because it may enhance job destruction in periods of decreasing demand such as the Great Recession. If competitive labor market theories hold, real wages should decline and involuntary unemployment should be reduced. In the low-inflation environment of the past years, with inflation rates between 1.1 and 2.5 %, real wage cuts (a wage increase smaller than the inflation rate) may even imply nominal wage cuts. However, if wage rigidity is present, downward adjustment of wages is limited and therefore involuntary unemployment will remain. Moreover, the degree and type of wage rigidity is an important determinant of economic policy. In case of Nominal Real Wage Rigidity (DNWR) monetary policy should aim at a positive rate of inflation (Akerlof et al., 1996) to “grease the wheels of the economy”, while in case of Downward Real Wage Rigidity (DRWR) inflation will not improve efficiency and the focus should be more on stable prices. Probably due to these implications, the research on wage rigidity has increased in the past 10 years. Especially the International Wage Flexibility Project (IWFP), a consortium of over 40 researchers, has led to new insights regarding the methodology to assess wage rigidity and regarding the magnitude of wage rigidity in various countries.

Although wage rigidity is an important topic and substantial research has been performed on wage rigidity in recent years, there is no full consensus in the literature yet regarding how to measure downward nominal and real wage rigidity. The concept is clear: if a worker is subject to real or nominal wage rigidity, he receives a real or nominal wage freeze, whereas he would have received a wage change below a certain threshold in case of fully flexible wages. In case of nominal rigidity this threshold is equal to zero. In case of real downward wage rigidity the threshold is equal to the inflation expectation. But although the concept is clear, different approaches to measure wage rigidity exist. The approaches differ, among other things, in the way they address measurement error. Although in general the amount of measurement error in administrative data is much smaller compared to survey data, the possibility of measurement error can still not be ignored. For example, in our data of monthly contractual wages measurement error can be present because firms may accidentally register bonuses and declarations as part of the base wage. Measurement error is an important issue in relation to the measurement of wage rigidity because it will lead to spurious (and sometimes negative) wage changes, which could lead to an underestimate of the amount of rigidity.

The paper focuses on the question which of the three methods commonly used in the literature for estimating wage rigidity is to be preferred: the simple IWFP approach, the model based IWFP approach and the Maximum Likelihood approach. In other words: which method or approach measures wage rigidity most precisely? In essence all methods try to estimate the extent of wage rigidity by inspecting deviations from the wage change distribution that would prevail in absence of wage rigidity, often called the notional distribution. This notional distribution is unobserved. All three models make their own assumptions on this notional distribution and all three models have their own approach as regards measurement error. The simple IWFP approach simply measures wage rigidity by dividing the number of wage freezes by the number of wage cuts as described in Dickens et al. (2007a). In this method the absence of measurement error is assumed. Second, the model based IWFP approach applies a two-stage Method of Moments estimator, as described in Dickens et al. (2007b). This method makes a measurement error correction based on the autocorrelation of wage changes. The third approach examines wage rigidity using a model which takes into account normally distributed measurement error. The model is estimated using a Maximum Likelihood method as discussed in Goette et al. (2007).

We estimate the three models on administrative panel data and empirically compare the results of the three methods. We use data from the Social Statistical files (SSB) for 2006-2012, containing monthly wage information for all jobs in the Netherlands. We focus on the year

to year changes in the monthly base wage for the month of October. Next to applying the three well known models, we carry out additional analyses to get insight in the impact of the assumptions behind these different models: for two models we release one of their assumptions and replace it by an assumption featuring in one of the other models. Moreover, we evaluate the three methods from a conceptual point of view and relate the differences in outcomes to the differences in assumptions behind the models.

One main finding is that the assumptions regarding the notional wage change distribution are an important determinant of the level of wage rigidity that is measured. We argue that the preferred model is the model based IWFP approach for two reasons. First, the model based approach has the most sophisticated method to take into account measurement error. Second, the model based approach assumes that the notional distribution of wage changes follows a two sided Weibull distribution, which is more realistic than a normally distributed notional wage change distribution, as is assumed by the Maximum Likelihood approach which may lead to an overestimation of DRWR in the Maximum Likelihood approach. Moreover, the simple IWFP approach is very sensitive to the specified rate of inflation, since the estimation of the inflation expectation is not incorporated in the model.

As an additional analysis we study the correlation between wage rigidity as measured by the three methods on the one hand and worker and firm characteristics on the other hand, using a fractional logit model. We find coherent results: the presence of wage rigidity is unevenly distributed among groups of workers: downward nominal and real wage rigidity in the Netherlands are positively related to a higher age, higher education, open-end contracts, full-time contracts and to working in a firm that experiences zero or positive employment growth.

Hence, although the three methods do not agree on the amount of rigidity, they agree for a large part on what variables are related positively or negatively to downward nominal and real wage rigidity. This is an indication that all three methods measure the same phenomenon, which implies that estimates of determinants of wage rigidity can be compared over countries using any of the three methods. However, for measuring the fraction of workers covered by downward nominal or real wage rigidity, the choice of the method matters.

Moreover, we contribute to the literature by providing accurate, internationally comparable estimates of wage rigidity in the Netherlands, based on administrative data. The only estimates available so far for the Netherlands are based on survey data. The overall picture that we find is that the Netherlands has a less than average amount of downward nominal wage rigidity compared to other countries. However, for downward real wage rigidity the results point at a level that is above average compared internationally. DRWR is higher in Belgium (known for its inflation compensation), France and Sweden, while Denmark, Italy, Germany, the UK and the US show a substantially lower DRWR.

The remainder of this paper is organized as follows: In Section 2 we explicate and compare the wage rigidity estimation methods and the underlying assumptions. Section 3 discusses the data, including the measure for wages that is used. Section 4 presents the results regarding the estimation of downward nominal wage rigidity (DNWR) and downward real wage rigidity (DRWR) and relates the variation in outcomes to the differences in assumptions behind the models. In Section 5 we analyse the determinants of wage rigidity and Section 6 concludes.

## 2 Methodology comparison

In the past years the methodology developed by the International Wage Flexibility Project (IWFP) has become the international standard for estimating wage rigidity. The IWFP uses two methods to assess the extent of DRWR and DNWR: a simple approach (Dickens et al., 2007a) and a model-based approach (Dickens et al., 2007b). A third method that as well has been developed especially to measure wage rigidity is the Maximum Likelihood method, as documented in Goette et al. (2007). All three methods focus on wage rigidity among job

stayers, i.e. workers that work for the same firm as the year before.

The literature on wage rigidity agrees on the definition of wage rigidity: all three main methods basically model wage rigidity as the fraction of workers reluctant to (either real or nominal) wage cuts (also called the fraction of workers covered by wage rigidity).

These methods assume that for part of the population of job stayers the bargaining process between employer and employee does not lead to the nominal or real wage cut that would result in case of fully flexible wages. Instead, it is supposed that they will agree upon a (real or nominal) wage freeze. The methods thus assume that a fraction of the wage changes that would have been located below a certain threshold if there was no rigidity, are instead located right at that threshold. It is assumed that the nominal rigidity threshold is the same for every individual, while the real rigidity threshold, normally the inflation expectation, is heterogeneous. This follows from the fact that the inflation expectations differ among workers. The inflation expectation is almost always modelled symmetrically.

Essentially, the three methods are looking for a heap of observations around or at a threshold and missing observations in the part below the threshold. The extent of wage rigidity is assessed by inspecting the difference between the observed wage changes and the wage changes that would occur absence of rigidity, but these obviously can not be observed. The methods use different assumptions on how the wage changes would have looked like in absence of rigidity. All methods, however, agree on the fact that the distribution is symmetric: the methods assume that the wage change distribution in absence of rigidity (notional distribution), below the median is a mirror image of the upper part. The methods are able to recover information on the notional distribution using this symmetry-assumption and information of wage changes above the rigidity thresholds (for those observations rigidity is not binding and the notional distribution is not affected by rigidity).

The approaches differ, among other things, in the way they address measurement error. Although in general the amount of measurement error in administrative data is much smaller compared to survey data, the possibility of measurement error can still not be ignored. For example, in our data of monthly contractual wages measurement error can be present because firms may accidentally register bonuses and declarations as part of the base wage. In our data, according to the model-based IWFP method, 83% of the jobs report the wage always without measurement error, for the other 17% an error is introduced in 82% of the cases. Measurement error is a serious issue when measuring wage rigidity because it causes spurious (and sometimes negative) wage changes. For example, if a wage actually remains constant in year  $t-1$ ,  $t$  and  $t+1$  but a reporting error is made in year  $t$ , then the wage changes in year  $t$  and year  $t+1$  differ from zero: in this example, the wage changes are equal but with opposite signs. The wage changes measured then give a sign of flexibility, whereas the actual wage is constant. This way, measurement error leads to an underestimation of the amount of downward wage rigidity, even in case the average measurement error is zero (with a positive standard deviation).

A broad outline of the three methods can highlight the main differences in assumptions. First, *the simple IWFP method* assumes that all wage freezes would have been wage cuts in absence of rigidity and estimates the “fraction of wages covered by rigidity” as the fraction of notional wage cuts that have become a wage freeze. This method is developed within the IWFP-framework as an easy way to estimate the degree of wage rigidity in a country. The advantage of this method is that it is simple and that it does not use assumptions on the shape of the notional distribution. The disadvantage, however, is that this method does not take measurement error into account. Second, *the model-based IWFP method* is developed to overcome this problem. The model-based IWFP method first corrects the distribution for measurement error, where it is assumed that measurement errors are two-sided Weibull distributed. This is done by using the fact that errors that are made in reporting wages, even in administrative data, lead to negative autocorrelation in the wage changes. E.g. if accidentally a high wage is reported this will cause a wage increase in the first period, while in the next period a wage decrease

is observed. After the correction for measurement error is made, the method estimates wage rigidity by comparing the observed distribution with a notional distribution, that is assumed two-sided Weibull. Third, also *the Maximum Likelihood method* takes into account measurement error. Again wage rigidity is modelled as the fraction of wage changes that would have been located below a certain threshold if there was no rigidity, but actually are located right at this threshold. This model assumes normally distributed measurement error and a normally distributed notional distribution, instead of the more complex and flexible two-sided Weibull distributions.

*The simple IWFP method* is based on asymmetries in the wage change distribution. For nominal rigidity it is assumed that all wage freezes would have been wage cuts if no rigidity was present. A fraction of those wage cuts, that would have prevailed in absence of rigidity, instead have received a wage freeze. Therefore, the fraction observations that have received a wage freeze, while they were scheduled for a wage cut can be used as estimate. The estimate is defined as:

$$p_{N,t}^c = \frac{f_{n,t}}{f_{n,t} + c_{n,t}}, \quad (1)$$

where  $f_{n,t}$  is the fraction of workers with nominal wage freezes and  $c_n$  is the fraction with nominal wage cuts. This estimate for DNWR ranges between 0 and 1 and is easily interpreted as the fraction of workers that are covered by Downward Nominal Wage Rigidity. This interpretation, however, is only correct if no DRWR is assumed, since the simple IWFP method estimates the probability of being covered by DNWR by inspecting the workers with nominal wage cuts and freezes. Therefore, the estimate of DNWR only gives information on those not covered by DRWR, since if they would have been covered by DRWR they would not have had a wage cut or freeze. Therefore, in fact the estimate of DNWR is the probability of being covered by DNWR, conditional on not being covered by DRWR. This notion is important in order to obtain comparability of definitions of DNWR over methods. To indicate that this probability is conditional on not being covered by DRWR, we have added a *c*-superscript.

For DRWR a similar measure is used:

$$p_{R,t} = \frac{f_{r,t}}{f_{r,t} + c_{r,t}}, \quad (2)$$

where  $f_{r,t}$  is the fraction of workers with real wage freezes (wage changes equal to the inflation rate the worker expects) and  $c_{r,t}$  is the fraction with real wage cuts (wage changes lower than the expected inflation rate). If the notional distribution is symmetric the fraction of wage freezes  $f_{r,t}$  can be determined by subtracting the part  $\lambda_t$  below the (mean) inflation expectation  $\pi_t$  from the symmetric counterpart  $v_t$  (the fraction of observations above  $M_t + (M_t - \pi_t)$ , where  $M_t$  is the median wage change in year  $t$ ). However, since the inflation expectation is heterogeneous across workers, firms and over the year, a part of the wage freezes will still be reported in the lower tail. For example, if an individual worker expects 2 % inflation, while the mean inflation expectation is 2.5 %, and this worker has a real rigid wage, the employer and employee could for example come to an agreement at a wage change of 2 % (the workers inflation expectation), while in absence of DRWR the employee would have had a wage change below this point. However, this wage change will still be reported in the lower tail and not be counted as someone with a rigid wage, because all observations below the mean inflation expectation (of 2.5 %) are part of the lower half: the part with the wage changes that are not downwardly real rigid. Dickens et al. implicitly assume in their paper that the distribution of the inflation expectation is symmetric, and that therefore half of the observations that are downwardly real rigid (50 %) would fall outside the lower part, but that the other 50 % would still fall inside the lower part. Therefore the difference between the upper and lower part is multiplied by 2 ( $f_{r,t} = 2(v_t - \lambda_t)$ ). The number of observations that would have had a real wage cut can be defined as the number of observations that would have been in the lower tail. Since this is equal to the number of

observations in the upper tail, we take  $f_{r,t} + c_{r,t} = v_t$ . This gives:

$$p_{R,t} = \frac{f_{r,t}}{f_{r,t} + c_{r,t}} = \frac{2(v_t - \lambda_t)}{v_t}. \quad (3)$$

It is important to note that this estimate cannot be constructed if the expected rate of inflation is higher than the median wage change. In that case, the lower part contains more than 50% of the observations. Now, the upper part, which would have also more than 50 % of the observations, would also contain observations that are affected by real wage rigidity. A disadvantage of the simple IWFP method is that the real rigidity threshold, the inflation expectation, has to be specified exogenously and is not identified by the method. A wrongly specified inflation expectation will therefore have consequences on the estimate of DRWR.

*The model-based IWFP method* consists of two steps. The first step is the error correction step, the second step is the estimation step. Both steps use the Method of Moments. The main problem when estimating wage rigidity is the fact that in almost all data sets the observed measure of wages is distorted by measurement error. The IWFP error correction procedure uses two assumptions about the errors:

- The only source of auto-correlation in wage changes is measurement error. Making an error and reporting a too high wage in year  $t$ , will result in a wage increase from year  $t - 1$  to  $t$  and a wage decrease from year  $t$  to  $t + 1$ .
- Errors are distributed according to a two-sided Weibull distribution.

Starting point for *the first step of the model-based IWFP method, which is the error correction step*, is a histogram of wage changes, where each ‘bin’ represents 1 percent of the observations of a particular year. The observed histogram is corrected for measurement error and subsequently wage rigidity is measured on the basis of the corrected histogram. The main advantage of this approach is that data sets with a lot of measurement error and data sets without measurement error do not lead to different results (in theory and also in practice according to Dickens et al. (2007b)). Without using this correction data sets with measurement error will find a lower degree of wage rigidity in general (since it causes spurious negative wage changes, which is a sign of wage flexibility). Note that the model-based method does not try to correct individual observations, but instead corrects the histogram. Using these assumptions it is possible to compute the fraction of observations for each cell (or ‘bin’) in the histogram that should be located in another cell. Using this information, the corrected distribution can be calculated, and subsequently wage rigidity can be measured.

The main goal of the error correction step is to find a transformation matrix  $\mathbf{R}_t$  to transform the observed histogram  $\mathbf{m}_t^o$  into the corrected histogram  $\mathbf{m}_t$  using

$$\mathbf{m}_t = \mathbf{R}_t^{-1} \mathbf{m}_t^o. \quad (4)$$

The elements in the matrix  $\mathbf{R}_t$  represent the fraction of observations in a certain cell in the histogram that switches to a different cell in the histogram. This matrix  $\mathbf{R}_t$  depends on the probability of not being prone to measurement errors ( $p_{ne}$ ), the probability of making an error conditional on being prone to measurement errors ( $p_{m|e}$ ) and the shape and scale parameters of the two-sided Weibull error distribution, denoted by  $a$  and  $b_t$ , respectively.  $a$ ,  $p_{ne}$ ,  $p_{m|e}$  are assumed constant, while  $b_t$  is time-dependent. To find those parameters, moment conditions are derived for the fraction of switchers. A switcher is defined as someone who had a wage change  $d_{i,t}^o > U_{t,q}$  and in the consecutive year  $d_{i,t+1}^o < L_{t,q}$  or where  $d_{i,t}^o < U_{t,q}$  and  $d_{i,t+1}^o > L_{t,q}$ . So switchers are workers who receive a wage change below (above) a threshold in year  $t$  and above (below) a threshold in year  $t + 1$ . Here  $U_{t,q}$  and  $L_{t,q}$  denote bounds for defining switchers using criterion  $q$ . We will use in total two criteria  $q$ , as defined by the IWFP procedure. The fraction of switchers is calculated as  $\sum_{i=1}^{N_{t,t+1}} \frac{h_{i,t,q}}{N_{t,t+1}}$ , where  $h_{i,t,q}$  is equal to one if observation  $i$

is a switcher in year  $t$  according to criterion  $q$ . These empirical moments should match their theoretical counterparts, which can be calculated using the parameters  $a, b_t, p_{ne}, p_{m|e}$ . To reduce the number of parameters,  $b_t$  is calculated as a function of the estimated auto-covariance. This leaves only  $a, p_{ne}, p_{m|e}$  left to be optimized by minimizing the weighted<sup>1</sup> distance between the theoretical and empirical moment conditions. We perform multiple random starts, in order to overcome local-minimum problems.

The model-based IWFP method uses multiple-dimensional integrals of the two-sided Weibull distribution. Since no analytical expressions are known for these integrals, we approximate them using Monte-Carlo integration. Here, we deviate from the methodology as defined by the original IWFP procedure, where Gauss-Legendre quadrature is used. We do this, since discontinuities at zero caused severe approximation problems.

Once the for measurement error corrected histogram is obtained, the amount of wage rigidity can be estimated. *The second step of the model-based IWFP method is the estimation step.* Estimation is done by minimizing the distance between the corrected histogram and the expected histogram, given the parameters for the distribution and the parameters denoting the amount of wage rigidity. In fact this is an attempt to fit the expected histogram, given the parameters, to the corrected histogram. This way we find the appropriate parameters especially with respect to the fraction of observations covered by wage rigidity. In Dickens et al. (2007b) the distance is weighted by the variance-covariance matrix of the histogram parameters in the error-correction step. Unfortunately, we cannot weigh with the variance-covariance matrix, since the derivation of the variance-covariance matrix requires numerical derivatives and we cannot calculate the derivatives of stochastic quantities (caused by the Monte-Carlo approximation) in a computationally feasible way.

The expected histogram is based on the assumption that (notional) wage changes follow a two-sided Weibull distribution. A fraction of the wage changes below the inflation expectation, receive a wage change equal to the inflation expectation instead. This is what Dickens et al. (2007b) call the real adjusted wage change. A fraction of the real adjusted wage changes that falls below zero will receive a (nominal) wage freeze instead. Using this model, and the parameters that have to be found, we calculate for each cell in the histogram what fraction of observations should be located in that bin. A detailed description of the calculation of the expected distribution is given below.

The notional wage change  $d_{i,t}^n$  is modelled as a draw from a two-sided Weibull-distribution. Now the real adjusted wage change can be derived as  $d_{i,t}^r$

$$d_{i,t}^r = \begin{cases} d_{i,t}^n & \text{if } \epsilon_{i,t}^r > p_{R,t} \\ \max(\pi_{i,t}, d_{i,t}^n) & \text{otherwise} \end{cases} . \quad (5)$$

where  $\pi_{i,t}$  is the inflation expectation (modelled as a normally distributed variable with mean  $\pi_t$  and variance  $\sigma_{\pi,t}^2$ ),  $\epsilon_{i,t}^r$  is an i.i.d. random variable that is drawn from a uniform distribution on the unit interval and  $p_{R,t}$  is the probability of being subject to DRWR. This means that the wage change equals the notional wage change if this observation is not subject to DRWR. If the observation is subject to DRWR, the wage change equals the maximum of the inflation expectation and the notional wage change. In other words, if the notional wage change is below the inflation expectation, the wage change equals the inflation expectation. Now the true wage change  $d_{i,t}$  is given by

$$d_{i,t} = \begin{cases} 0 & \text{if } d_{i,t}^r \leq 0 \text{ and } \epsilon_{i,t}^n < p_{N,t}^c \text{ or } (-.01 \leq d_{i,t}^r \leq .01 \text{ and } \epsilon_{i,t}^1 < p_{s1,t}) \\ & \text{or } (-.02 \leq d_{i,t}^r < -.01 \text{ or } .01 < d_{i,t}^r \leq .02 \text{ and } \epsilon_{i,t}^2 < p_{s2,t}) \\ d_{i,t}^r & \text{otherwise} \end{cases} , \quad (6)$$

<sup>1</sup>In Dickens and Goette (2005) equation 3 states that one should weigh with the variance-covariance matrix of the empirical moments, but we believe that this is a typographical error and we should weigh with the inverse of this variance-covariance matrix to follow the GMM literature (it can be proved that this is the optimal weighting matrix).

where  $\epsilon_{i,t}^n$ ,  $\epsilon_{i,t}^1$  and  $\epsilon_{i,t}^2$ , are all uniform distributed random variables with support on the unit interval,  $p_{N,t}^c$  is the probability of being subject to downward nominal rigidity and  $p_{s_1,t}$  and  $p_{s_2,t}$  are the probability of being subject to symmetric nominal rigidity (menu costs). In essence this equation states that the wage change equals zero if the wage change, where real rigidity is already taken into account, is below zero and the observation is subject to DNWR, or if the observation is subject to symmetric rigidity and the wage change is between -2 % and 2 %.

Using this model the expected distribution can be calculated by determining the theoretical moments. Now the distance between the empirical moments and the theoretical moments can be minimized. This can be seen as fitting the histogram. The model-based IWFP method is discussed at length in Dickens and Goette (2005). A cross-check on the model-based approach was performed by Lunnemann and Wintr (2010) and they conclude that “the results are fairly robust not only with regard to the approach used to delimit measurement error, but also over time.”

Similar to the simple IWFP method, the model-based IWFP method defines the probability of being covered by DNWR for the distribution where real wage rigidity is already taken into account (Dickens et al. (2007b) call this the ‘real adjusted distribution’). In essence the model-based method uses the same technique as the simple one and assumes that wages below the zero bin end up in the zero bin if they are covered by DNWR. Dickens et al. state: “Such workers who have a notional wage change of less than zero, and who are not subject to downward real wage rigidity, receive a wage freeze instead of a wage cut.” Again, the estimate of DNWR only gives information on those not covered by DRWR, since if they would have been covered by DRWR they would not have been located in the zero bin or in the bins below zero (they would not have had a wage cut or freeze). Therefore, also in the model-based IWFP method the estimate of DNWR is the probability of being covered by DNWR, conditional on not being covered by DRWR.

*The Maximum Likelihood method* is based on the assumption that a job can be in only one out of three regimes each year: the flexible regime, the nominal rigidity regime and the real rigidity regime with probability  $p_{F,t}$ ,  $p_{N,t}$  and  $p_{R,t}$  respectively. Moreover, it is assumed that wage changes are generated according to a linear combination of covariates ( $\mathbf{x}_{i,t}/\beta$ ) and a normally distributed error term (with mean 0 and variance  $\sigma_{\omega,t}^2$ ). We will use gender, age, company size, part-time employment<sup>2</sup> and year- and sector-dummies as covariates. Now in the nominal rigidity regime wage changes  $d_{i,t}^n$  below zero are not allowed and wages will be set to zero according to:

$$d_{i,t} = \begin{cases} d_{i,t}^n & \text{if } d_{i,t}^n \geq 0 \\ 0 & \text{if } d_{i,t}^n < 0 \end{cases} \quad (7)$$

If the notional wage change is below zero in this regime it is said that the observation is ‘constrained’. If the notional wage change is above 0, the observation is categorized as ‘unconstrained’. If people are covered by downward real wage rigidity, wages are generated according to<sup>3</sup>:

$$d_{i,t} = \begin{cases} d_{i,t}^n & \text{if } d_{i,t}^n \geq \pi_{i,t} \\ \pi_{i,t} & \text{if } d_{i,t}^n < \pi_{i,t} \end{cases} \quad (8)$$

The cut-off  $\pi_{i,t}$  below which the wage change becomes rigid is modelled as heterogeneous, since inflation expectations may differ over the year and per individual.  $\pi_{i,t}$  is modelled as normally distributed with mean  $\pi_t$  and variance  $\sigma_\pi^2$ . If the notional wage change is below the inflation expectation  $\pi_{i,t}$  in this regime it is said that the observation is ‘constrained’. If the notional wage change is above  $\pi_{i,t}$ , the observation is unconstrained. The observed wage change  $d_{i,t}^o$  is assumed to be corrupted by measurement error. Goette et al. their method assumes that

<sup>2</sup>The Netherlands has the highest percentage of part-time workers. According to Eurostat 50 % of the employees works part-time

<sup>3</sup>Goette et al. (2007) state that wages in the real rigidity regime are set to zero if the wage change is below  $\pi_{i,t}$ , but this appears to be a small typographical error



errors are normally distributed with mean 0 and variance  $\sigma_m^2$  and that only a fraction of the observations contains errors. The probability of making an error is defined as  $p_m$  and a wage change can contain either zero errors (with probability  $(1 - p_m)^2$ ), one error (with probability  $2p_m(1 - p_m)$ ) or two errors (with probability  $p_m^2$ ). This leads to a total of 15 regimes, which are shown in Table 1.

**Table 1:** Regimes of the Maximum Likelihood method (Goette et al., 2007, Technical Appendix)

	Flexible	Real Rigidity		Nominal Rigidity	
		Constrained	Unconstrained	Constrained	Unconstrained
No Error	F0	RC0	RU0	NC0	NU0
One Error	F1	RC1	RU1	NC1	NU1
Two Errors	F2	RC2	RU2	NC2	NU2

This model can be cast into a likelihood function and this function can be maximized. Most derivations for the likelihood contributions of the 15 regimes ( $P_{XY}$ ) are given in the Technical Appendix for Goette et al. (2007). The Berndt-Hall-Hall-Hausman (BHHH) algorithm is used to maximize the complete likelihood function. The probability of a measurement error  $p_m$  is bound to lie between 0 and 0.5 and the mean inflation expectation  $\pi_t$  is bound between 0 and 0.05. The likelihood is optimized for all years at once, where  $\beta, \sigma_\omega^2, \sigma_\pi^2, \sigma_m^2$  and  $p_m$  are constant over time, while  $p_{R,t}, p_{F,t}, p_{N,t}$  and  $\pi_t$  are year-dependent.

## 2.1 Comparison of methods

All three methods model wage rigidity in the same way, but use different approaches and assumptions, especially on the notional and error distribution. The most important characteristics and assumptions are summarized in Table 2. The most notable difference is that the model-based IWFP method and the Maximum Likelihood method both take measurement error into account, while the simple IWFP method does not. Since we know that measurement errors are present, even in administrative data, this is a weakness of the simple IWFP method. On the other hand, the simple IWFP method uses the least restrictive assumptions on the notional distribution.

**Table 2:** Comparison of the three methods

	Simple IWFP method	Model-based IWFP method	Maximum Likelihood method
Identification method	Dividing wage cuts by wage freezes	Correcting the distribution and fitting a model on the corrected histogram	Maximum Likelihood
Notional distribution	Symmetric	Two-sided Weibull	Normal
Notional distribution depends on observed characteristics	No	No	Yes
Error distribution	Does not take errors into account	Two-sided Weibull	Normal
Identification of errors	Does not take errors into account	Uses autocorrelation of wage changes of an individual	Assumes observations are independent
Incorporates symmetric rigidity	No	Yes	No

An assumption that all three methods have in common is that the wage change distribution, in absence of rigidity, is symmetric around the median. For the simple IWFP model this is the only assumption made about this so called notional wage change distribution. The model-based IWFP method and the Maximum Likelihood method assume a particular, again symmetric, notional distribution. Testing this assumption of symmetry is problematic since the notional distribution is not observed. However, Card and Hyslop (1997) state that “Although there is no a priori reason for imposing assumption 1<sup>4</sup>, we believe that symmetry is a natural starting point for building a counterfactual distribution.” Furthermore, they argue that if the wage determination process is stationary, than the wage change distribution in absence of rigidity is symmetric. Another argument for using the symmetry assumption is found in Dickens and Goette (2005), where the authors state that “The lower tail, in countries where real rigidity does not appear to be much of a problem, seems to be a mirror image of the upper tail for those parts that are above zero when the distribution is not affected by real rigidity.” If one does not want to use the symmetry assumption, one needs to assume that the shape of the wage change distribution is constant over time. This assumption is used in Kahn (1997).

The model-based based method and Maximum Likelihood method make additional assumptions about the notional distribution of wage changes. The model-based IWFP method assumes that notional wage changes are two-sided Weibull distributed, while the Maximum Likelihood methods assumes that wage changes come from a normal distribution. In Goette et al. (2007) a normal distribution is chosen. In Dickens et al. (2007a) the normality assumption is criticized: “an analysis of Gottschalk’s estimates of true wages, suggests that wage changes have a distribution that is both more peaked and has fatter tails than the normal”. Dickens et al. (2007a) give some arguments for assuming a two-sided Weibull: “A Weibull distribution will provide a good approximation to the distribution if, instead, workers’ raises are based on sequential standards, where only those who meet all prior standards are considered for the next level, and at each level, rewards increase exponentially.” In addition Lunnemann and Wintr (2010) state that “This choice is based on the observation that the distribution of wage changes is typically more peaked and has fatter tails than the normal distribution.” Kátay (2011) gives similar arguments “The motivation behind using a two-sided Weibull distribution is that a typical wage change distribution clearly diverges from the normal distribution even at the right tail unaffected by rigidity: workers’ wage changes are tightly clustered around the median change, which makes the distribution much more peaked with fatter tails compared to the normal.” The Maximum Likelihood method is the only method which uses explanatory variables to construct the notional distribution. This has the advantage that heterogeneity is, partially, taken into account.

Also the assumptions on the error distribution differ. Where the simple IWFP method does not take errors into account at all, the ML method assumes that they are normally distributed. The model-based IWFP method assumes that errors are two-sided Weibull distributed. In Dickens and Goette (2005) this assumption is substantiated as follows: “This structure for the error – the two-sided Weibull with a fraction of people never making errors – was chosen to match the distribution of estimated errors in Gottschalk’s data. His estimated errors had a distinctly peaked distribution and showed some auto-correlation in the probability of an error that was simply accounted for by having a group of people who didn’t make errors.” Furthermore the model-based IWFP method uses the autocorrelation that is caused by measurement errors to identify the extent of measurement error. The Maximum Likelihood method assumes that all observations are independent and does not use this property.

All three methods have their own strengths and weaknesses. In an ideal situation we would propose to combine the strengths of the various methods by identifying two-sided Weibull-distributed measurement error using the autocorrelation in the wage changes and let the two-sided Weibull distributed notional distribution depend on observed characteristics. As an at-

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<sup>4</sup>The assumption that the notional distribution is symmetric

tempt to integrate the strong points of the different methods we have tried to adapt the Maximum Likelihood method to allow for a two-sided Weibull wage change and error distribution. However, it turned out that this is infeasible since analytical expressions for the required integrals of two-sided Weibull distributions are not available. This would mean that for every observation and iteration the integrals should be approximated numerically. Given our large sample size (26,601,768 observations) this is not feasible, unfortunately. It would be an interesting topic for further research.

However, if we have to make a choice for a particular method, then we would choose the model-based IWFP method. Although this method does not take heterogeneity in wage changes into account, the notional distribution is flexible and more realistic than the normal distribution of the Maximum Likelihood method. Furthermore this method takes measurement error into account and uses additional information (autocorrelation) to identify it. A second-best would be the Maximum Likelihood method which also accounts for measurement error.

The DNWR-estimates of the IWFP methods and the Maximum Likelihood method can not be compared directly. Both IWFP methods estimate the probability of being covered by DNWR by inspecting the workers with nominal wage cuts and freezes. Therefore, these estimates of DNWR only give information on those not covered by DRWR, since if they would have been covered by DRWR they would not have had a wage cut or freeze. In fact, here DNWR can be interpreted as the probability of being covered by DNWR, conditional on not being covered by DRWR. The Maximum Likelihood method however, assumes that observations can be in only one out of three regimes (the flexible regime, the nominal rigidity regime or the real rigidity regime). Here the regime probabilities add up to unity by construction. This clearly is not a conditional probability. To make our estimates comparable with each other, we will also report DNWR estimates for the Maximum Likelihood method according to the definitions of the IWFP, since this definition is used most often in the literature. Hence, we calculate the probability of being covered by nominal wage rigidity, conditional on not being covered by real wage rigidity as follows:

$$P_{N,t}^c = \frac{P_{N,t}}{P_{F,t} + P_{N,t}} = \frac{P_{N,t}}{1 - P_{R,t}} \quad (9)$$

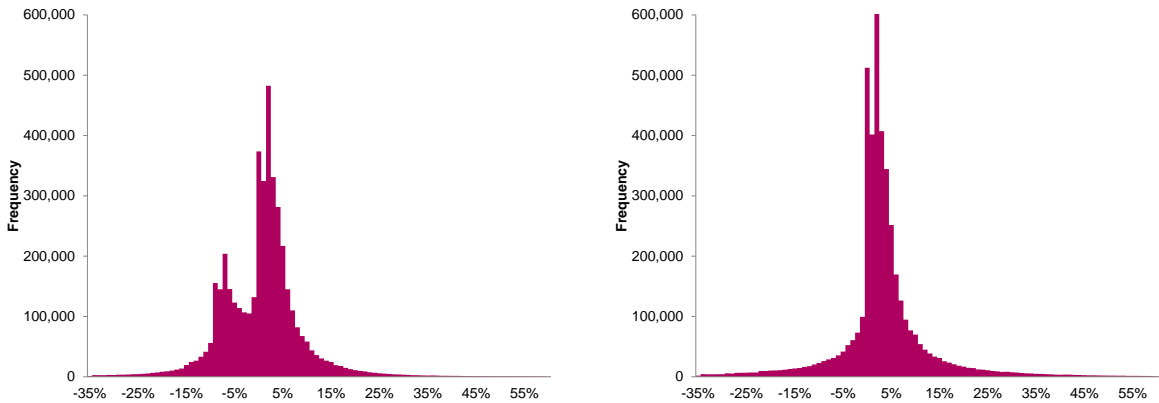
### 3 Data

Data from the Social Statistical files (SSB) for the Netherlands regarding the years 2006-2012 is used. The wage data is based on the policy administration of the Employee Insurances Implementing Agency (UWV). In this data set wage information is available per month (for most of the observations). The data set does also contain information on salaried hours ('verloonde uren'). Furthermore various characteristics of the employees and their jobs are available, ranging from the obtained level of education to contract type.

Regarding wage changes different measures could be used. The most common measures focus on hourly wages or annual earnings. Within the IWFP both are used (Dickens et al., 2007a). The procedure for correcting measurement errors and estimating rigidity is slightly different for both measures. Often annual earnings are converted to hourly wages (Dickens et al., 2007a; Du Caju et al., 2007). However it is widely acknowledged (Dickens et al., 2007a; Lunnemann and Wintr, 2010; Gottschalk, 2005) that measures for hours worked are imprecise.

In Lunnemann and Wintr (2010) hourly workers (employees who get paid by the hours worked) and salaried workers (employees who get paid a fixed salary per month or year) are distinguished. Regarding salaried workers, when no wage change takes place, dividing their salary by the actual hours worked could lead to spurious wage changes. Regarding hourly workers, when their actual number of hours worked changes while the salary is not divided by the hours worked, the data may as well report a spurious wage change. Lunnemann and Wintr (2010) discuss this problem in detail. Statistics Netherlands makes no distinction between

hourly workers and salaried workers. Lunnemann and Wintr (2010) encountered the same problem for Luxembourg and decide to call someone a salaried worker if the monthly salary variation is smaller than their hourly variation. We did experiment with hourly wages. These hourly wages clearly showed in some years that a part of the wage changes were shifted<sup>5</sup>. This artefact stems from the fact that the number of working days in a month depends on the day of the week by which the month started. Some companies report hours worked as based on these actual working days, while others apparently use some form of norm hours. The distortion can be clearly seen from Figure 1. Compared to the distribution of monthly wage changes in Figure 1a, the distribution of hourly wages (Figure 1b) contains an extra spike at the left hand side due to firms that report an increase in actual working hours because October 2012 contains more working days (opposed to weekend-days) than October 2011, while the salary is not sensitive to this change in working days. Furthermore, hourly workers are very uncommon in the Netherlands. For these reasons we do not divide wages by the number of hours worked. In this study, we focus on the year to year changes in the monthly base wage for the month of October. In October no specific incidental wage changes take place, which could distort our estimates. Using monthly in stead of hourly wages prevents us from introducing measurement errors. However, measurement error will to some extent still be present in our data, for example because firms may accidentally register bonuses and declarations as part of the base wage. According to the model-based IWFP method 83% of the jobs report the wage always without measurement error, for the other 17% an error is introduced in 82% of the cases.



(a) Observed hourly wage change distribution      (b) Observed monthly wage change distribution

Source: own calculations based on Statistics Netherlands microdata

**Figure 1:** Histograms of the observed wage change distributions in 2012

**Table 3:** Descriptive statistics of the observed wage change distributions

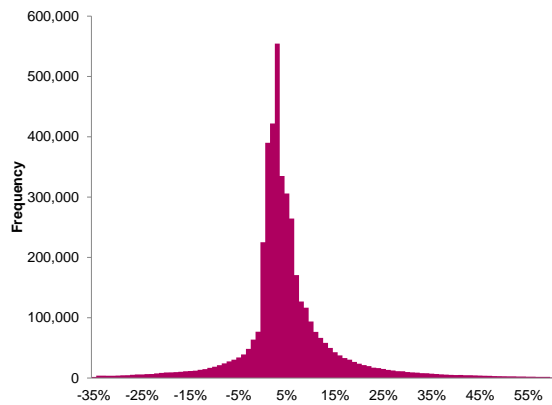
Year	N	Mean	Median	Skewness	Kurtosis	SD	$d_o < 0$	$d_o < \hat{\pi}_{ML}$	$d_o < \hat{\pi}_{CEP}$
2007	4431928	0.054	0.034	2.149	108.955	0.224	16%	33%	25%
2008	4489885	0.058	0.042	1.978	115.405	0.213	15%	34%	33%
2009	4609207	0.038	0.029	1.498	139.087	0.206	20%	42%	31%
2010	4652883	0.030	0.015	2.338	149.772	0.206	21%	45%	49%
2011	4626283	0.032	0.021	1.143	136.259	0.187	20%	41%	49%
2012	4388473	0.033	0.023	0.226	154.240	0.189	19%	42%	46%

Source: own calculations based on Statistics Netherlands microdata

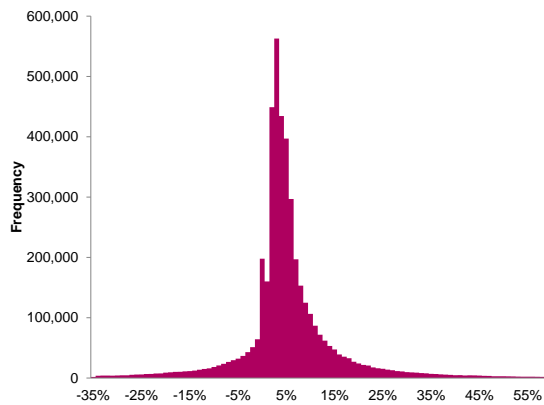
To make the estimates comparable with other studies we confine the analysis to job-stayers. In some previous studies part-timers are removed from the sample<sup>6</sup>, but part-time work is

<sup>5</sup>With for example an additional spike at -8 % in the wage change histogram

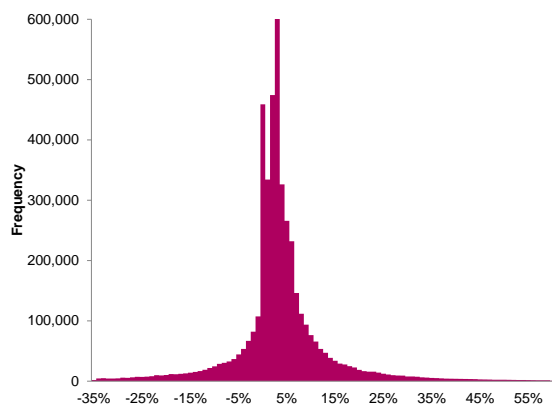
<sup>6</sup>For example: Messina et al. (2010), Du Caju et al. (2007)



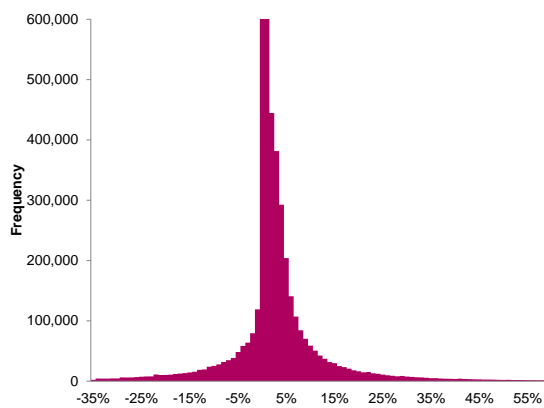
(a) 2007



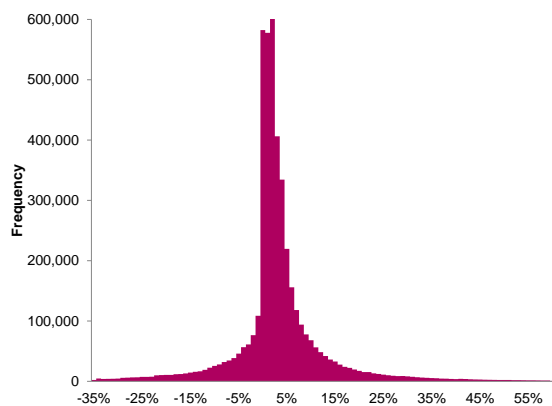
(b) 2008



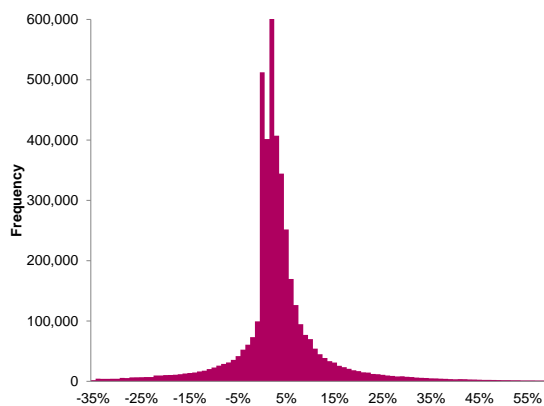
(c) 2009



(d) 2010



(e) 2011



(f) 2012

Source: own calculations based on Statistics Netherlands microdata

**Figure 2:** Histograms of the observed wage change distributions

very common in the Netherlands (more than half of all employees is a part-time workers) we do not remove those observations. Furthermore we remove some implausible observations. Wage cuts of more than 35 % and wage increases of more than 60 % in the simple IWFP and Maximum Likelihood method, since those observations are unlikely to reflect valid wage changes. Furthermore Dickens et al. (2007a) use the same bounds. This reduces our sample with 2 %. For the model-based IWFP we do not delete these observations to follow Dickens et al. (2007b). Jobs of less than 12 hours a week are removed, since those observations do not have a significant impact on the company level and, moreover, the number of hours worked fluctuates. Interns, temporary workers, director and major shareholders, people in the Social Employment Law (WSW) and on-call staff are removed, since those employees do not negotiate or are not considered employees. Lastly, employees below 23 and above 64 years old are removed from the dataset. The employees below 23 often work next to their study, while the amount of hours worked fluctuates. People above 64 are not included because of retention effects (like retention bonuses etc.), which could distort true wage changes.

Table 3 presents descriptive statistics on the distribution of the observed wage changes. The mean wage change is clearly higher before the great recession (2007 and 2008) than in the subsequent years. The mean wage change exceeds the median wage change in every year, pointing at a positive skewness of the distribution. The skewness-statistic shows some variation over the years, which is confirmed by the fact that in Figure 2 the tail on the right side of the distribution is fatter in some years. The kurtosis-statistic shows that the distributions are less peaked in the years before the great recession than in more recent years and also the standard deviation has come down a bit. So the overall picture is that the wage change distribution has become more compressed. The last three columns of Table 3 present the percentage of observations on the observed wage change that are below the zero percent threshold, the heterogeneous inflation expectation estimated using the Maximum Likelihood model and the at that time published inflation forecast. The share of observations that remain below the zero percent threshold is higher in the more recent period, which is in line with the fact that the mean and the median have come down, hence the entire distribution is located more to the left compared to 2007 and 2008. Also a larger share remains below the inflation expectation, which may partly be explained by the fact that inflation expectations were lower in the more recent period. In the Appendix, Table ?? gives additional descriptive statistics for males and females separately, as well as for full-time and part-time workers. Compared to men, women have a more skewed and less peaked wage change distribution. Since part-time work is largely concentrated among female workers, this difference may be related to the flatter distribution of part-time workers.

## 4 Results and Discussion

The fraction of workers that we find to be covered by downward nominal wage rigidity and downward real wage rigidity respectively varied over the different estimation methods (Table 4 and 5). The first column shows estimates based on *the simple IWFP method*. Instead of using at that time published forecasts for the inflation expectation we use the estimated inflation expectation according to our Maximum Likelihood approach, for reasons of consistency. Overall, the simple IWFP method measures a substantial amount of DNWR (23 %). The estimates of DRWR, with an average of 10 %, are overall lower than those of DNWR. The estimate of DRWR in 2009 is less than zero. This is possible in the IWFP method if the area under the upper half is slightly smaller than the area under the lower half. This points at the absence of DRWR in 2009. The results of the simple IWFP method indicate a low amount of real rigidity. These results are in line with our expectations of the Dutch labour market where wage moderation is common.

The second column of Table 4 and 5 presents the results for *the (adapted) model-based IWFP method*, where we have set the amount of symmetric rigidity to zero. Here we deviate from the

**Table 4:** The fraction of workers covered by Downward Nominal Wage Rigidity

Year	Simple IWFP	Model-based IWFP (adapted)	ML (unconditional)	ML (conditional)	Model-based IWFP (original)
2007	0.13	0.12	0.10	0.40	0.01
2008	0.08	0.06	0.06	0.26	0.05
2009	0.24	0.23	0.19	0.48	0.16
2010	0.38	0.38	0.32	0.74	0.24
2011	0.26	0.25	0.19	0.61	0.17
2012	0.29	0.29	0.22	0.60	0.12
Mean	0.23	0.22	0.18	0.52	0.12
SD	0.11	0.12	0.09	0.17	0.09

Source: own calculations based on Statistics Netherlands microdata

**Table 5:** The fraction of workers covered by Downward Real Wage Rigidity

Year	Simple IWFP	Model-based IWFP (adapted)	ML	Model-based IWFP (original)
2007	0.33	0.45	0.76	0.52
2008	0.14	0.55	0.78	0.60
2009	-0.13	0.25	0.61	0.31
2010	0.09	0.24	0.57	0.25
2011	0.03	0.33	0.69	0.39
2012	0.13	0.26	0.64	0.27
Mean	0.10	0.35	0.67	0.39
SD	0.15	0.13	0.08	0.14

Source: own calculations based on Statistics Netherlands microdata

original model-based IWFP procedure. Symmetric rigidity allows wage changes above -2 % and below 2 % to be rounded to zero. This might be reasonable in a high-inflation environment, but not in this case where the inflation is sometimes as low as 1.5 %. Symmetric rigidities stem from the fact that employers do not want to make small adjustments, due to administrative costs of these change (similar to menu costs). The adapted model-based IWFP method estimates that 22 % of the workers is covered by DNWR and 35 % is covered by DRWR. For reasons of completeness, the results without this restriction (in accordance with the original model-based IWFP method) are presented in column 5 of Table 4 and column 4 of Table 5.

The results of *the Maximum Likelihood method* are presented in the third and fourth column of Table 4 and the third column of Table 5. The fraction of observations in the nominal rigidity regime is estimated at 18 %. However, the fraction of workers covered by DNWR, conditional on not being covered by DRWR amounts to 52 %. Hence, the conditional fraction, calculated for reasons of comparability with the IWFP-methods, is substantially higher than the fraction found by the IWFP-methods. Moreover, according to the Maximum Likelihood method DRWR equals 67 % in the Netherlands. This seems to be an implausibly high fraction. Related to this, the Maximum Likelihood method results in a standard deviation of the inflation expectation of 1.28 %. This means that about 10 % of all workers expect a negative inflation rate, which is not very plausible either.

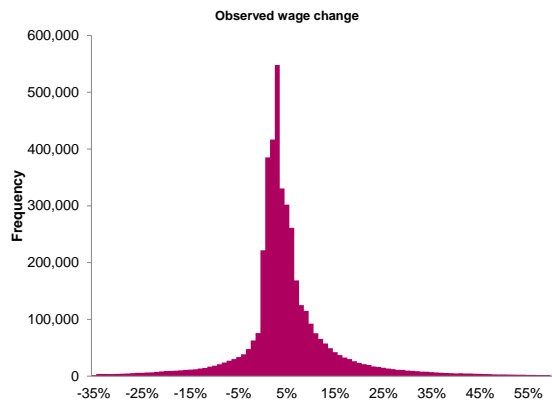
When diving further into the ML-approach, it seems that the relatively high fraction of workers covered by DRWR probably is a consequence of the normality assumption of the notional wage change distribution. This is demonstrated by a simulation exercise that is presented in Figure 3. This simulation exercise is similar to the one performed in Devicienti et al. (2007). The observed distribution is shown in Figure 3a. Using the estimated parameters it is possible to simulate wage changes. First the notional wage change is depicted in Figure 3b. Then for every observation an inflation expectation is simulated, using the estimated parameters, which is shown in Figure 3c. Subsequently, for every observation the regime it belongs to is

drawn using the estimated regime probabilities and wages are set accordingly. After adding measurement error, the result is the distribution from Figure 3d. The simulated distribution looks almost identical to the observed distribution. This is a sign that this model is able to replicate most of the properties of the observed wage change distribution. However, it is obvious that the notional distribution is much less peaked than the simulated and observed distribution. Dickens et al. (2007a) states that wage changes follow a two-sided Weibull distribution. If that statement is correct, notional wage changes are two-sided Weibull distributed and the normality assumption falls short. It is well-known that the two-sided Weibull distribution is more peaked than the normal distribution and has fatter tails. This might have a large influence on the results, especially if the inflation is close to the median wage change. In that case, for observations around the median the likelihood contribution for the free regime is lower according to the normal distribution than when a two-sided Weibull distribution would have been used. Intuitively this makes sense: since the probability density function of the two-sided Weibull is higher around the median, it is more peaked. That means that observations around the median are more likely when the notional distribution is two-sided Weibull, than when notional wage changes are normally distributed, since the likelihood is higher for those observations. The use of a normal distribution as is done in the ML-approach will probably lead to an underestimate of the likelihood of observations falling in the free regime, since around the median relatively many observations deviate from the notional distribution. This leads to a lower estimated probability of belonging to the free regime ( $P_{F,t}$ ) and therefore to an overestimate of the probability of belonging to the real rigidity regime. Therefore, the high amounts of DRWR that we measure using the ML-method do not come as a surprise, since, as discussed in Section 2 the normality assumptions might not hold and our period of observation is characterized as a low inflation period with an inflation rate close to the median, especially for the years 2009-2012.

We present some additional analyses to get insight in the impact of the assumptions behind the different models: for two models we will release one of its assumptions and replace it by an assumption featuring in one of the other models. This way we can identify what is the impact of this assumption. First, the model-based IWFP-method is applied using a normally distributed notional distribution instead of the two-sided Weibull-distribution. Second, the Maximum Likelihood method is repeated but now with a notional distribution not depending on worker characteristics. Table 6a shows that if normality is assumed for the notional distribution in the adapted model-based IWFP method, the measured downward real wage rigidity is much higher than when the original (Weibull) distribution is assumed. We now find that 72 % of the workers is covered by downward real wage rigidity, which is similar to the results for the Maximum Likelihood method (67 %). This points at the normality assumption being indeed an important determinant of the high DRWR found by the Maximum Likelihood method, which assumes normality for the notional distribution. For the downward nominal wage rigidity the results do not change by applying a different notional distribution to the model-based method, because the ratio of the number of wage freezes and the number of wage cuts (which can be detected easily by counting them) is not very sensitive to the assumptions regarding the notional distribution. In contrast, for assessing the level of DRWR the number of freezes at the expected inflation threshold has to be estimated using the peak in the distribution, which differs according to the assumed shape of the notional distribution.

The fact that the measurement of nominal wage rigidity is less sensitive to the assumed notional distribution raises the question why the Maximum Likelihood method finds a higher result for downward nominal wage rigidity compared to the model-based method (both with a normal and a two-sided Weibull distributed notional distribution). This probably is the case because the Maximum Likelihood method 'thinks' that part of the negative wage changes are generated by measurement error. Since the method assumes that measurement errors are distributed symmetrically, it might be that the fat right tail of the wage change distribution can only be explained by measurement error, since the assumed normal notional distribution

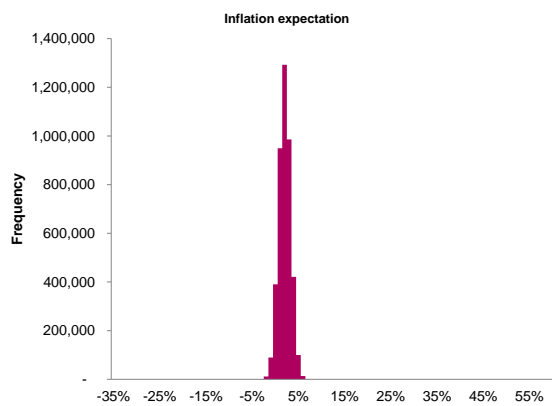




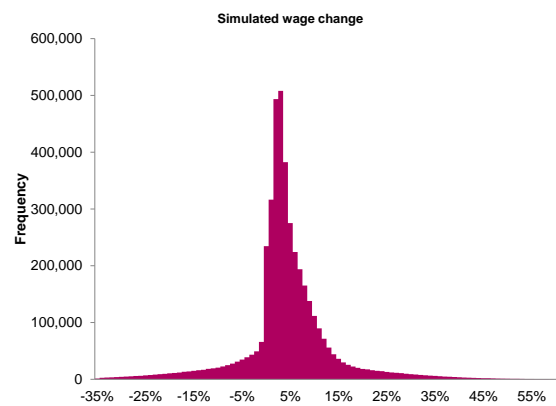
(a) Observed wage change distribution



(b) Simulated notional wage change distribution



(c) Simulated inflation expectation distribution



(d) Simulated wage change distribution

Source: own calculations based on Statistics Netherlands microdata

**Figure 3:** Histograms of the simulated, observed and notional distribution for 2007, obtained using the Maximum Likelihood method

does not have fat tails. The model-based method does not suffer from this problem, since in the estimation step it is assumed that the obtained histogram does not contain any measurement error anymore due to the correction based on autocorrelation.

We have tested this hypothesis, and it appears to be valid. When we make the probability of making an error negligible small, the amount of DNWR measured is 29 %, slightly more than the amount found by the simple and model-based IWFP method. The results are shown in Table 6b.

Next, Table 6c presents the results for the Maximum Likelihood method when using a notional distribution that does not depend on observed characteristics. In comparison with Table 4 and 5 the results are fairly similar. It might be that notional wage changes are very homogeneous and that therefore adding characteristics does not alter the results.

**Table 6:** Results of the additional analyses

(a) Results of the adapted model-based IWFP method using a normal notional distribution

Year	DNWR	DRWR
2007	0.11	0.75
2008	0.07	0.75
2009	0.21	0.74
2010	0.35	0.67
2011	0.24	0.69
2012	0.26	0.74
Mean	0.20	0.72
SD	0.09	0.03

(b) Results of the Maximum Likelihood method assuming no errors

Year	DNWR (conditional)	DRWR
2007	0.17	0.78
2008	0.05	0.69
2009	0.31	0.71
2010	0.50	0.65
2011	0.36	0.72
2012	0.38	0.71
Mean	0.29	0.71
SD	0.16	0.04

(c) Results of the Maximum Likelihood method using a notional distribution that does not depend on observed characteristics

Year	DNWR (conditional)	DRWR
2007	0.40	0.74
2008	0.26	0.76
2009	0.48	0.61
2010	0.74	0.57
2011	0.61	0.68
2012	0.61	0.63
Mean	0.52	0.66
SD	0.15	0.07

Source: own calculations based on Statistics Netherlands microdata

When comparing the results of the various models the variation in outcomes is notable. Estimates of wage rigidity differ largely, especially regarding DRWR. While the simple IWFP method detects 10 % of real wage rigidity and the the model-based IWFP method 35 %, the Maximum Likelihood method estimates the fraction of wages set under the real rigidity regime as high as 67 %. For the amount of nominal rigidity, the amount of wage rigidity measured by the simple IWFP method and the model-based IWFP method is similar (23 % and 22 % respectively), but the conditional fraction obtained by the Maximum Likelihood method largely deviates (52 %). The divergence of the results illustrates that the results are sensitive to the different distributional assumptions made. The simple IWFP method only assumes symmetry of the notional distribution, the model-based IWFP method assumes that

wages are distributed according to a two-sided Weibull distribution in absence of rigidity, while the Maximum Likelihood method assumes normality but allows the notional to depend on observed characteristics.

As discussed in the second section, the literature emphasizes that the normality assumption is not very realistic, since the distribution of wage changes is supposed to be more peaked and has fatter tails than the normal distribution. Our empirical analysis convincingly shows that the results are sensitive to the distributional assumptions regarding the notional wage change distribution. The Maximum Likelihood method measures a much higher level than the model based IWFP method. Applying the normality assumption to the adapted model-based IWFP method, the measured downward real wage rigidity is much higher than when the original (Weibull) distribution is assumed. We therefore argue that the normality assumption in the Maximum Likelihood approach most probably leads to an overestimation of DRWR. A drawback of the simple IWFP approach is that the measurement of wage rigidity is very sensitive to the specified rate of inflation, since the estimation of the inflation expectation is not incorporated in the model. Also, the simple model does not take into account measurement errors. The model-based approach has the most sophisticated method to take into account measurement error. Given these empirical results we conclude that the model-based IWFP approach is the preferred model of the three.

We find that, irregardless of the method used, the estimates of DNWR and DRWR differ over the years. The simple IWFP model even presents negative estimates of the fraction of wages set under the real rigidity regime, pointing at the absence of DRWR. Another interesting observation is the fact that, according to all methods, DNWR is lower in 2007 and 2008 compared to 2009-2012, while DRWR -according to the model-based and ML estimates- is substantially higher in 2007 and 2008 than in subsequent years. In 2007 and 2008 the estimated inflation expectation of both the model-based and Maximum Likelihood method was considerably higher than the years thereafter. In theory the estimates of wage rigidity should not depend on the inflation expectation, which would imply that the amount of DNWR has increased after 2008. However, Bauer et al. (2007) also find this pattern and attribute this finding to the theory of Akerlof et al. (2000) that “when inflation is low, a significant number of people may ignore inflation when setting wages and prices.” This might be the case for the Netherlands as well.

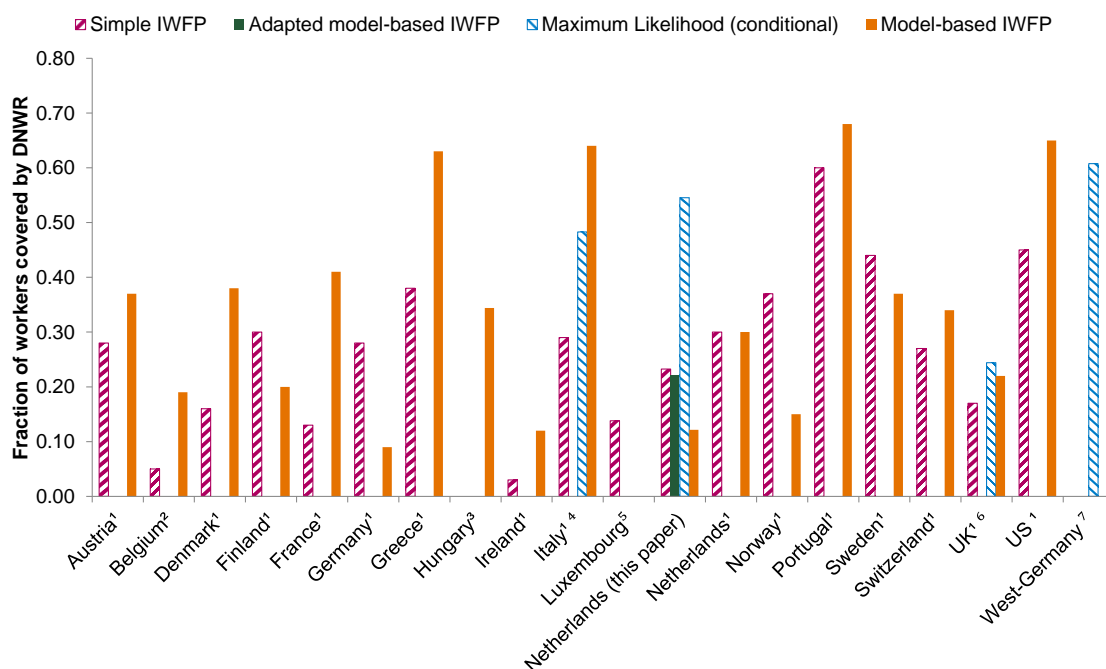
In order to compare our estimates internationally, Figure 4 and Figure 5 present estimates for several countries based on various recent papers. It is important to note that the time period of different estimates is not (always) equal. The adapted model-based method for The Netherlands can be compared to the model-based estimates for other countries. The need to adapt the model raised from the fact that we measure wage rigidity in the Netherlands for a low inflation period. The results for the other countries were measured in periods less recent period, with higher inflation.

The first thing to notice is that within countries estimates according to the three discussed methods vary substantially. This is in line with our findings for the Netherlands. A part of the variability might be explained by the fact that the time periods and data sets of the various method differ. However, the differences between the IWFP methods and the Maximum Likelihood method appear to be smaller for other countries than for our data, especially with respect to DNWR: the Maximum Likelihood estimate of DNWR lies in between those of the model-based and simple IWFP method for the UK and Italy. This might be partially explained by the fact that in our period of observation the inflation was relatively low, which might lead to a situation where the inflation is close to the median; as discussed before this might lead to an overestimate of DRWR by the Maximum Likelihood method.

In Table 7 we have ranked the estimates. From this figure we can see that although the estimates might differ, both IWFP methods produce a quite similar ranking. The Pearson rank correlation coefficient is 0.46 and 0.72 for DNWR and DRWR, respectively for the IWFP methods. The Pearson rank correlation for the ML estimates and the model-based IWFP

method is 0.72 for real wage rigidity. For nominal rigidity the Pearson rank correlation is negative. However, note that these two correlation coefficients are based on a small number of observations.

The overall picture that we find is that the Netherlands has a less than average amount of downward nominal wage rigidity compared to other countries. However, for downward real wage rigidity the results of both our preferred model-based IWFP method and the Maximum Likelihood method point at a level that is more than average internationally. DRWR is higher in Belgium (known for its inflation compensation), France and Sweden, while Denmark, Italy, Germany, the UK and the US show a substantially lower DRWR.



<sup>1</sup> Dickens et al. (2007a) and Dickens et al. (2007b) (Figure 3 and Figure 4, respectively)

<sup>2</sup> Du Caju et al. (2007) (Table 3 and Table 6)

<sup>3</sup> Kátay (2011) (Non-technical summary)

<sup>4</sup> Devicienti et al. (2007) (Table 3 - Average (benchmark estimates))

<sup>5</sup> Lunnemann and Wintr (2010) (Table 2)

<sup>6</sup> Barwell and Schweitzer (2007) (Table 1)

<sup>7</sup> Bauer et al. (2007) (Average of Table 1)

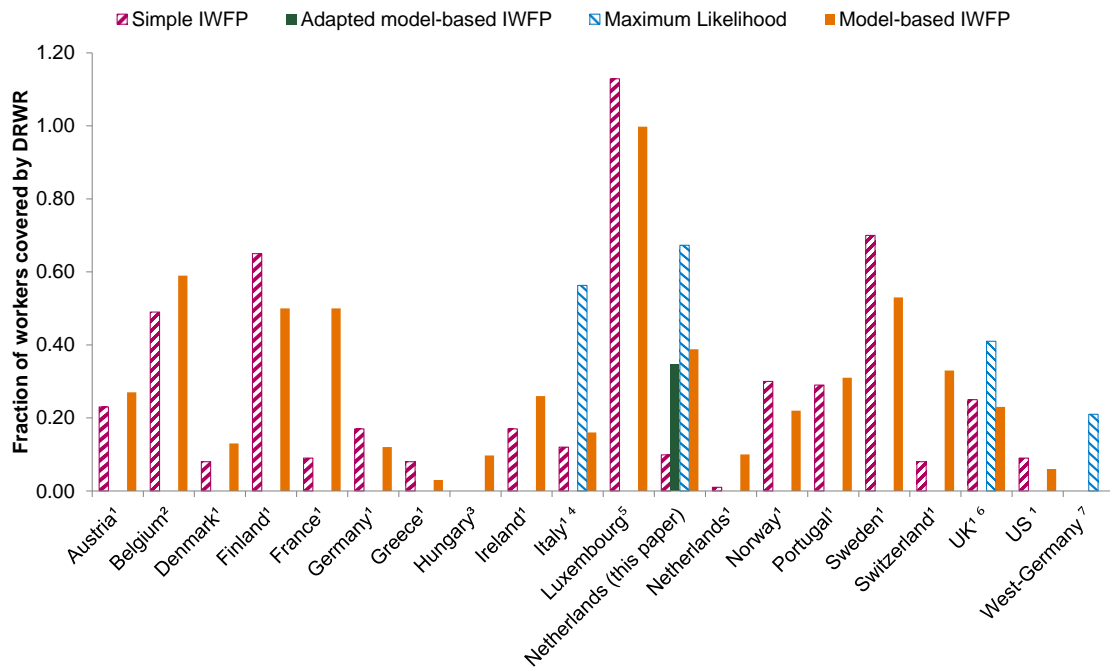
Note: We have converted unconditional probabilities of ML studies to conditional probabilities in order to make the estimates comparable.

Source for our results: own calculations based on Statistics Netherlands microdata

**Figure 4:** The estimated degree of Downward Nominal Wage Rigidity (DNWR) in various countries

## 5 Wage rigidity and worker-firm characteristics

Having established the estimates for wage rigidity, the next step is to analyse the differences in DNWR and DRWR across groups. Similar to Messina et al. (2010) a fractional logit model is estimated and marginal effects are reported, where the probability of real or nominal wage rigidity is the dependent variable and individual or firm characteristics are used as independent



<sup>1</sup> Dickens et al. (2007a) and Dickens et al. (2007b) (Figure 3 and Figure 4, respectively)

<sup>2</sup> Du Caju et al. (2007) (Table 3 and Table 6)

<sup>3</sup> Kátay (2011) (Non-technical summary)

<sup>4</sup> Devicienti et al. (2007) (Table 3 - Average (benchmark estimates))

<sup>5</sup> Lunnemann and Wintr (2010) (Table 2)

<sup>6</sup> Barwell and Schweitzer (2007) (Table 1)

<sup>7</sup> Bauer et al. (2007) (Average of Table 1)

Source for our results: own calculations based on Statistics Netherlands microdata

**Figure 5:** The estimated degree of Downward Real Wage Rigidity (DRWR) in various countries

**Table 7:** Ranking of various wage rigidity estimates for different countries from high to low

DNWR			DRWR		
Simple IWFP	Model-based IWFP	ML (conditional)	Simple IWFP	Model-based IWFP	ML
Portugal	Portugal	West-Germany	Luxembourg	Luxembourg	<b>Netherlands<sup>a</sup></b>
US	US	<b>Netherlands<sup>a</sup></b>	Sweden	Belgium	Italy
Sweden	Italy	Italy	Finland	Sweden	UK
Greece	Greece	UK	Belgium	Finland	West-Germany
Norway	France		Norway	France	
Finland	Denmark		Portugal	<b>Netherlands<sup>ab</sup></b>	
Netherlands	Sweden		UK	<b>Netherlands<sup>ac</sup></b>	
Italy	Austria		Austria	Switzerland	
Austria	Hungary		Ireland	Portugal	
Germany	Switzerland		Germany	Austria	
Switzerland	Netherlands		Italy	Ireland	
<b>Netherlands<sup>a</sup></b>	<b>Netherlands<sup>ac</sup></b>		<b>Netherlands<sup>a</sup></b>	UK	
UK	UK		France	Norway	
Denmark	Finland		US	Italy	
Luxembourg	Belgium		Switzerland	Denmark	
France	Norway		Denmark	Germany	
Belgium	<b>Netherlands<sup>ab</sup></b>		Greece	Netherlands	
Ireland	Ireland		Netherlands	Hungary	
	Germany			US	

<sup>a</sup> Estimates of this paper

<sup>b</sup> According to the original model-based IWFP specification

<sup>c</sup> According to the adapted model-based IWFP specification

Estimates collected from Dickens et al. (2007a,b); Du Caju et al. (2007); Kátay (2011); Devicienti et al. (2007); Lunnemann and Wintr (2010); Bauer et al. (2007). Estimates in bold are estimates of this paper (Source: own calculations based on Statistics Netherlands microdata). Earlier published estimates for The Netherlands (not bold) were carried out on survey data.

variables. It is important to note that the marginal effects of categorical variables are defined as the change from the base level. Furthermore, the definition of modal wage here does not originate from a statistical modal, but a modal as determined by the government (it is related to the Health Insurance Act (*Zorgverzekeringswet*)). In 2012, for example, the modal income was €33,000. In all regressions sector and year dummies are included to incorporate sector- and time-specific heterogeneity. We have information on education for one third of the observations and information on profit is available for about one third of the companies. Note that this analysis does not provide causal effects since some variables may be endogenous. For example, it is possible that wage rigidity causes less profit for companies and therefore companies with less profit have more wage rigidity. This study only gives a first glance at what underlying relations might be in the data. Researching causal relations could be the subject of a next study. This, however, is challenging since it is difficult to come up with strong instrumental variables.

For the simple and model-based IWFP method, note that estimates for wage rigidity concern samples instead of individuals, since the wage rigidity estimation is based on the histogram of wage changes for the entire sample or for a sub-sample. Du Caju et al. (2007) study differences across groups of workers by performing the model-based IWFP procedure on a selection of the dataset, for example by performing the IWFP procedure on a sub-sample of women. Dickens et al. (2007a) uses bivariate correlations between rigidity measures and explanatory variables. The results of these studies, in contrast to Messina et al. (2010), are difficult to interpret since they probably suffer from an omitted variable bias (OVB). For example, by applying the IWFP procedure on a group with a high income and on a group with a low income, one may erroneously conclude that a high income is strongly positively correlated with wage rigidity. However it is very well possible that for example age is correlated with income and that in reality differences in rigidity are explained by age.

We improve upon these comparisons between groups as they have been performed in the literature by introducing a different approach. We apply the IWFP model to sub-samples, where each sub-sample contains observations for which multiple variables are equal, e.g. *gender=male*, *age=25-45*, *wage=1 - 2 × modal income*. Since it would be technically infeasible in terms of computation time to work with groups for which all available explanatory variables are equal, we use in each regression one variable of interest and a fixed set of control variables, and the sample is split accordingly. We are able to use this procedure since our data set is large (26,601,768 observations), therefore splitting the sample into several groups will still give reliable estimates per group. Although with this approach there still is a chance of an omitted variable bias, the impact is minimized. Furthermore, this method is not sensitive to the critique of Dias et al. (2013) that the regressors in the logit model are based on all workers instead of just the workers scheduled for a wage cut. In our approach, in each group for which the wage rigidity is estimated the observed characteristics of those who are scheduled for a wage cut and those who are not are identical by construction. Therefore determination of the regressors on the basis of all workers or just the workers scheduled for a wage cut is interchangeable. To make this approach feasible for the model-based IWFP method the number of groups is reduced by considering only the 6 largest sectors (instead of all 14). Furthermore, we do not estimate the parameters of the error-correction step for each group separately, but instead perform the error correction step using the parameters previously obtained for the entire sample. For the Maximum Likelihood model, a straightforward way to study the determinants of wage rigidity would be to allow the degree of wage rigidity to depend on the explanatory variables we are interested in and reestimate the model. However, given our sample size and the number of parameters to estimate ( $\pm 130$ , including years of observation) this is technically infeasible. Therefore, we will perform the analysis using only 10 % of the observations and constrain the parameters of the notional distribution, the inflation expectation, the error probability and the error distribution at the values estimated previously on the entire sample. We estimate the probability of being in a certain regime on explanatory variables using a logit specification. In this analysis the IWFP definition for the amount of DNWR (the conditional probability  $P_{N,t}^c$ ) is used instead of the unconditional probability  $P_{N,t}$ . This makes the results of the fractional logit models comparable to those of the IWFP-methods.

The results for the simple IWFP procedure are presented in (Table 8). Company size is negatively associated with DNWR, while there is a positive correlation with DRWR. Age has is positively correlated with DNWR. Differences over gender are small. A high wage is positively correlated with both DNWR and DRWR. Another interesting effect is that working in a shrinking sector province combination is associated with a lower amount of DRWR<sup>7</sup>. This might indicate that workers are to some extent willing to accept real wage cuts in favour of employment. Furthermore, the results indicate that highly educated workers are prone to wage rigidity.

Regarding the results for the model-based IWFP method (Table 9) the most notable observation is that the estimated marginal effects show a lot of symmetry with the results of the simple IWFP method. Larger companies again show less DNWR but more DRWR. High wages are associated with more nominal and real wage rigidity, as does a high education and being female, although the latter effect is rather small. Working on fixed-end contracts and part-time contracts goes along with less wage rigidity. Working in a sector and province with shrinking employment again is associated with low DRWR. The effects of profit, employment growth and bonus culture of the firm and of workers originating from a foreign country are very small. A higher age is associated with both more DNWR and DRWR now, so only for DNWR the sign is the same as for the simple IWFP-model. Overall, the differences in marginal effects between the

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<sup>7</sup>We did use shrinkage, profit and employment growth indicators in the year of the wage change. In Du Caju et al. (2007) a robustness analysis is performed and it is shown that using lagged indicators do not lead to substantially different results.

**Table 8:** Wage rigidity and worker-firm characteristics in the Netherlands; Marginal Effects for the simple IWFP method

		DNWR		DRWR	
		dy/dx		dy/dx	
<b>Controls</b>					
Age	25-35				
	36-50	0.061	(0.000042)	-0.184	(0.000146)
	51-65	0.083	(0.000055)	-0.213	(0.000185)
Gender	Male				
	Female	0.002	(0.000057)	0.080	(0.000142)
Wage	< 1 × modal				
	1 – 2 × modal	-0.016	(0.000050)	0.078	(0.000148)
	> 2 × modal	0.056	(0.000095)	0.159	(0.000249)
Contract type	Open-end				
	Fixed-end	-0.010	(0.000063)	0.043	(0.000196)
Company size	Small				
	Medium	-0.233	(0.000065)	0.082	(0.000176)
	Large	-0.285	(0.000064)	0.062	(0.000161)
<b>Other explanatory variables</b>					
Hours	Full-time				
	Part-time	-0.072	(0.000058)	-0.141	(0.000155)
Profit	< 0				
	≥ 0	-0.010	(0.000077)	0.030	(0.000274)
Province/Sector	Normal/Growth				
	Shrinkage	0.025	(0.000051)	-0.079	(0.000159)
Employment growth	≥ 0				
	< 0	-0.004	(0.000075)	-0.017	(0.000201)
Bonus culture	Ratio < $Q_{25}$				
	$Q_{25} \geq$ Ratio < $Q_{75}$	0.021	(0.000094)	0.028	(0.000215)
	Ratio ≥ $Q_{75}$	-0.028	(0.000079)	0.042	(0.000185)
Country of origin	The Netherlands				
	Other	0.000	(0.000055)	-0.009	(0.000152)
Education	Low				
	Middle	0.021	(0.000096)	-0.015	(0.000296)
	High	0.028	(0.000113)	0.022	(0.000323)

Note: dy/dx for factor levels is the discrete change from the base level. In this table the results of 7 regressions are shown: each time all control variables are included and one explanatory variable. All regressions included a sector and a year dummy to incorporate sector- and time-specific heterogeneity. Robust standard errors in parenthesis. The simple IWFP method estimates indicators for wage rigidity at the group level; groups have been weighted by their size in this regression; the number of jobs times the number of years is about 26 million observations.

Source: own calculations based on Statistics Netherlands microdata



**Table 9:** Wage rigidity and worker-firm characteristics in the Netherlands; Marginal Effects for the model-based IWFP method

		DNWR		DRWR	
		dy/dx		dy/dx	
<b>Controls</b>					
Age	25-35				
	36-50	0.061	(0.000046)	0.022	(0.000122)
	51-65	0.076	(0.000061)	0.058	(0.000150)
Gender	Male				
	Female	0.017	(0.000061)	0.038	(0.000134)
Wage	< 1× modal				
	1 – 2× modal	-0.028	(0.000051)	0.016	(0.000130)
	> 2× modal	0.046	(0.000095)	0.117	(0.000205)
Contract type	Open-end				
	Fixed-end	-0.011	(0.000065)	-0.011	(0.000166)
Company size	Small				
	Medium	-0.203	(0.000052)	0.045	(0.000128)
	Large	-0.275	(0.000049)	0.018	(0.000118)
<b>Other explanatory variables</b>					
Hours	Full-time				
	Part-time	-0.095	(0.000058)	-0.007	(0.000135)
Profit	< 0				
	≥ 0	-0.011	(0.000070)	0.023	(0.000175)
Province/Sector	Normal/Growth				
	Shrinkage	0.010	(0.000063)	-0.065	(0.000140)
Employment growth	≥ 0				
	< 0	0.007	(0.000082)	0.008	(0.000075)
Bonus culture	Ratio < $Q_{25}$				
	$Q_{25} \geq$ Ratio < $Q_{75}$	-0.013	(0.000173)	0.046	(0.000237)
	Ratio ≥ $Q_{75}$	-0.009	(0.000128)	0.018	(0.000191)
Country of origin	The Netherlands				
	Other	-0.014	(0.000056)	-0.004	(0.000121)
Education	Low				
	Middle	0.021	(0.000103)	0.020	(0.000223)
	High	0.037	(0.000125)	0.057	(0.000263)

Note: dy/dx for factor levels is the discrete change from the base level. In this table the results of 7 regressions are shown: each time all control variables are included and one explanatory variable. All regressions included a sector and a year dummy to incorporate sector- and time-specific heterogeneity. Robust standard errors in parenthesis. The model based IWFP method estimates indicators for wage rigidity at the group level; groups have been weighted by their size in this regression; the number of jobs times the number of years is about 26 million observations.

Source: own calculations based on Statistics Netherlands microdata

**Table 10:** Wage rigidity and worker-firm characteristics in the Netherlands; Marginal Effects for the Maximum Likelihood method

	Controls + 1 Explanatory variable		All variables	
	DNWR dy/dx	DRWR dy/dx	DNWR dy/dx	DRWR dy/dx
<b>Controls</b>				
Age				
25-35	0.102 (0.000027)	0.136 (0.000130)	0.066 (0.000142)	0.131 (0.000269)
36-50	0.139 (0.000031)	0.185 (0.000142)	0.102 (0.000228)	0.183 (0.000388)
51-65				
Gender				
Male	0.028 (0.000027)	0.008 (0.000115)	0.060 (0.000170)	0.018 (0.000285)
Female				
Wage				
< 1 × modal	-0.011 (0.000026)	-0.006 (0.000106)	0.020 (0.000167)	-0.016 (0.000280)
1 – 2 ×	0.228 (0.000069)	0.000 (0.000265)	0.164 (0.000299)	-0.041 (0.000496)
> 2 × modal				
Contract type				
Open-end	0.005 (0.000039)	-0.027 (0.000161)	0.000 (0.000199)	-0.054 (0.000340)
Fixed-end				
Company size				
Small	-0.333 (0.000035)	0.124 (0.000161)	-0.222 (0.000212)	0.091 (0.000391)
Medium	-0.435 (0.000032)	0.111 (0.000165)	-0.405 (0.000193)	0.072 (0.000405)
Large				
<b>Other explanatory variables</b>				
Hours				
Full-time	-0.136 (0.000029)	-0.117 (0.000128)	-0.146 (0.000172)	-0.121 (0.000355)
Part-time				
Profit				
< 0	-0.040 (0.000072)	0.009 (0.000199)	-0.033 (0.000176)	0.008 (0.000292)
≥ 0				
Province/Sector				
Normal/Growth	0.043 (0.000028)	-0.028 (0.000097)	0.004 (0.000174)	-0.018 (0.000286)
Shrinkage				
Employment growth				
≥ 0	-0.008 (0.000037)	-0.020 (0.000144)	-0.027 (0.000222)	-0.037 (0.000404)
< 0				
Bonus culture				
Ratio < $Q_{25}$	0.034 (0.000038)	-0.005 (0.000139)	0.020 (0.000240)	0.102 (0.000418)
$Q_{25} \geq$ Ratio < $Q_{75}$	-0.016 (0.000038)	0.050 (0.000127)	0.050 (0.000248)	0.081 (0.000320)
Ratio $\geq$ $Q_{75}$				
Country of origin				
The Netherlands	0.018 (0.000038)	0.004 (0.000117)	-0.014 (0.000168)	-0.021 (0.000303)
Other				
Education				
Low	0.039 (0.000087)	0.009 (0.000233)	0.059 (0.000176)	0.026 (0.000386)
Middle	0.084 (0.000100)	0.038 (0.000253)	0.131 (0.000216)	0.072 (0.000421)
High				

Note: dy/dx for factor levels is the discrete change from the base level. In the left specification the results of 7 regressions are shown: each time all control variables are included and one explanatory variable. In the right specification the results of a regression are shown, where all variables are included. All regressions included a sector and a year dummy to incorporate sector- and time-specific heterogeneity. Clustered standard errors in parenthesis. The ML method estimates indicators for wage rigidity at the job level; the number of jobs times the number of years is about 26 million observations.  
Source: own calculations based on Statistics Netherlands microdata

two IWFP-methods appear to be smaller for DNWR than for DRWR. This is not surprising, since nominal wage freezes are much easier to detect than real wage freezes and, as previously shown, estimates of the amount of DRWR also differ between both IWFP methods. It is important to note that the standard errors are difficult to interpret, since these do not take into account the uncertainty in the estimates of DNWR and DRWR in the first stage. Weighting with the group size *and* the standard-errors of the estimates, would probably lead to incorrect standard errors since the standard errors of the first stage dependent on the group size. Therefore, a practical solution could be to bootstrap the entire process<sup>8</sup>. However given our sample size, bootstrapping the entire process is computationally infeasible (500 replications would take approximately 500 hours for the simple IWFP method and about 10 years for the model-based IWFP method). Therefore we have not weighted with the obtained standard errors.

For the Maximum Likelihood method we present two types of results. The results in the first column of Table 10 refer to regressions which contain the variable of interest plus a set of control variables. These results are comparable to those presented in Table 8 and 9. In the second column marginal effects are presented for the model specification that contains all explanatory variables. The presented standard errors allow clustering per individual. The results of the first Maximum Likelihood specification show similarity with the marginal effects of the model-based IWFP method. Since the amount of rigidity is probably overestimated by the ML method, the marginal effects for the ML method will in general be larger. Both methods find a clear positive correlation between age and being covered by DNWR and DRWR. In line with the two IWFP methods, the ML method finds a negative relation with company size and DNWR, while having a small positive effect on DRWR. Part-time contracts and fixed-end contracts are again associated with a lower degree of wage rigidity. In line with the IWFP-models it is found that a high education goes along with an increased probability of being covered by DNWR and DRWR. Working in a sector and province with shrinking employment again is associated with low DRWR, while negative employment growth in the firm is associated with less nominal and real wage rigidity, in line with our findings for the IWFP-methods.

Regarding the smaller effects there are notable differences between the Maximum Likelihood method and the model-based IWFP method. As discussed before, the Maximum Likelihood might overestimate the amount of real and nominal rigidity, this might also have an effect on the marginal effects. Another possible explanation is that the Maximum Likelihood method allows the notional distribution to depend on characteristics as age, while the IWFP methods do not take these effects into account. When comparing the two Maximum Likelihood specifications, the differences are small. Most interesting are the results for people who work in a company with an average bonus culture. The first specification shows that people working in a company with more than average bonus culture have less DNWR and more DRWR. The second specification however, estimates that these employees have a higher amount of DNWR and a lower amount of DRWR. A possible explanation could be that bonus culture is strongly correlated with one of the other explanatory variables, not being the control variables. In that case, the coefficient of bonus culture will compensate for the effect of the omitted control variable in the first specification, while this is not the case in the specification where all variables are included.

The overall picture that emerges from the analysis of the determinants of wage rigidity, taking into account the results of the three models, is that DNWR and DRWR are positively related to a higher age, higher education, open-end contracts, full-time contracts and to working in a firm that experiences zero or positive employment growth. Probably these groups are characterized by a stronger bargaining position which enables them to prevent nominal and real wage cuts better than younger, lower educated workers, workers on fixed-end and/or part-time contracts and workers in firms that were contracting. Stricter employment protection for long-tenured (and so often older) workers and workers on open-end contracts may be one of the explanations. Moreover, we find a positive but small correlation between being a female

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<sup>8</sup>We thank B. Wouterse and S.B. Gerritsen for this suggestion

worker and wage rigidity. All three methods find that working in a large firm is related to higher DNWR and lower DRWR. Large companies probably have more room to replace workers that are reluctant to accept a nominal wage cut, while small companies might be dependent on specific skills of specific employees. Moreover, all three methods find that working in a sector-province combination with shrinking employment is associated with lower DRWR. This might indicate that workers are to some extent willing to accept real wage cuts in favour of employment. Finally, a high wage is found to be positively related to both DNWR and DRWR according to the two IWFP-methods and to DNWR according to the ML-method. The fact that wages of  $1 - 2\times$  modal income are nominally less rigid than the reference group that earns less than the modal wage may be explained by lower wages following the statutory minimum wage, that is nominally rigid by definition in this period of observation. Other variables, for example of the firms' bonus culture and the country of origin of workers, generally show very small correlations.

Unfortunately, our data does not contain any information on the degree of organisation. Descriptive statistics on the degree of organisation, based on the (much smaller) Dutch Labour Force Survey Sociaal-economische Raad (2013) shows that the degree of organisation of employees increases over age groups, over company size and is relatively high among full-time workers and workers on open-end contracts. The similarity between these highly organised groups and the characteristics that are positively related to wage rigidity, suggests that being highly organised may be an omitted variable that is behind the ability of these specific groups to prevent wage cuts more successfully than other groups. All in all the results give the impression that the groups that are better protected and better organised have a higher ability to resist wage cuts. This contrasts with the finding by the OECD that "The slowdown in the growth rate of earnings was fairly evenly spread across the earnings distribution" OECD (2014).

The fact that the three methods show similar correlations with worker and firm characteristics is an indication that all three methods measure the same phenomena. Although the methods do not agree on the amount of rigidity, they agree for a large part on what has a positive or negative relation with DNWR and DRWR. This implies that estimates of correlations between wage rigidity and worker and firm characteristics can be compared over countries. However, for the Maximum Likelihood method only estimates in a similar inflation environment (low or high) can be compared, since we did find indications that this method overestimates the amount of real and nominal rigidity in case of a low inflation environment. However, for measuring the fraction of workers covered by DNWR and DRWR, the choice of the method is important.

## 6 Conclusion

The three commonly used methods for estimating wage rigidity differ substantially with respect to their methodology, and as a consequence also with respect to the amount of rigidity they measure. A main challenge in measuring wage rigidity is that the wage change distribution that would prevail in the absence of wage rigidity, the notional distribution, is unobserved. In the model-based IWFP method it is assumed that the notional distribution is given by a two-sided Weibull distribution. Deviations from this distribution are seen as rigidities. The Maximum Likelihood method however, assumes that wages are distributed normally without error and deviations from this distribution are seen as rigidities.

One main finding is that the assumptions regarding the notional wage change distribution are an important determinant of the level of wage rigidity that is measured. We argue that the model-based IWFP approach is the preferred model of the three. First, the model based-approach has the most sophisticated method to take into account measurement error. Second, the model-based approach assumes that the notional distribution of wage changes is follows a two sided Weibull distribution, which is more realistic than a normally distributed notional

wage change distribution, as is assumed by the Maximum Likelihood approach. Based on both our conceptual analysis and our empirical findings we argue that the normality assumption in the Maximum Likelihood approach most probably leads to an overestimation of DRWR. A drawback of the simple IWFP approach is that the measurement of wage rigidity is very sensitive to the specified rate of inflation, since the estimation of the inflation expectation is not incorporated in the model. Also, the simple model does not take into account measurement errors.

As an additional analysis we study the correlation between wage rigidity as measured by the three methods on the one hand and worker and firm characteristics on the other hand, using a fractional logit model. We find coherent results: the presence of wage rigidity is unevenly distributed among groups of workers: downward nominal and real wage rigidity in the Netherlands are positively related to a higher age, higher education, open-end contracts, full-time contracts and to working in a firm that experiences zero or positive employment growth.

Hence, although the three methods do not agree on the amount of rigidity, they agree for a large part on what variables have a positive or negative relation with downward nominal and real wage rigidity. This is an indication that all three methods measure the same phenomenon, which implies that estimates of determinants of wage rigidity can be compared over countries using any of the three methods. However, for measuring the fraction of workers covered by downward nominal or real wage rigidity, the choice of the method matters.

Besides, we contribute to the literature by providing accurate, internationally comparable estimates of wage rigidity in the Netherlands, based on administrative data. The only estimates available so far for the Netherlands were based on survey data. The overall picture that we find is that the Netherlands has a less than average amount of downward nominal wage rigidity compared to other countries. However, for downward real wage rigidity the results of both our preferred model-based IWFP method and the Maximum Likelihood method point at a level that is above average compared internationally. DRWR is higher in Belgium (known for its inflation compensation), France and Sweden, while Denmark, Italy, Germany, the UK and the US show a substantially lower DRWR.

A limitation of this study is that it confines itself to wage rigidity among job stayers. The literature on displaced workers shows that dismissed workers in general earn lower wages in their post-displacement jobs (Deelen et al., 2014).

Moreover, this study sheds no light on other mechanisms that are used by companies to adjust their costs in times of decreasing demand. A decomposition of how companies reduce the size of their wage bill, as done for Belgium in Fuss (2009), might give more insights in how companies adapt to decreasing demand and might also give an indication of wage rigidity. Lastly our research did not focus on causal relations. Studying causes of wage rigidity is an interesting next step. This step, however, is challenging since it is difficult to come up with strong instrumental variables.

## References

- Akerlof, G., Dickens, W. T., and Perry, G. L. (2000). TD et Perry, GL 2000. Near-Rational Wage and Price Setting and the Optimal Rates of Inflation and Unemployment. *Brookings Papers on Economic Activity*.
- Barwell, R. D. and Schweitzer, M. E. (2007). The Incidence of Nominal and Real Wage Rigidities in Great Britain: 1978–98. *The Economic Journal*, 117(524):F553–F569.
- Bauer, T., Bonin, H., Goette, L., and Sunde, U. (2007). Real and Nominal Wage Rigidities and the Rate of Inflation: Evidence from West German Micro Data. *The Economic Journal*, 117(524):F508–F529.

- Card, D. and Hyslop, D. (1997). Does inflation “grease the wheels of the labor market”? In *Reducing inflation: Motivation and strategy*, pages 71–122. University of Chicago Press.
- Deelen, A., De Graaf-Zijl, M., and Van den Berge, W. (2014). Labour market effects of job displacement for prime-age and older workers. *CPB Working Paper (Forthcoming)*.
- Devicienti, F., Maida, A., and Sestito, P. (2007). Downward Wage Rigidity in Italy: Micro-Based Measures and Implications. *The Economic Journal*, 117(524):F530–F552.
- Dias, D., Marques, C., and Martins, F. (2013). The determinants of downward wage rigidity: some methodological considerations and new empirical evidence. *Banco de Portugal Economic Bulletin*, (Autumn 2013).
- Dickens, W. and Goette, L. (2005). Estimating Wage Rigidity for the International Wage Flexibility Project. *mimeo, Brookings Institution*, pages 1–20.
- Dickens, W., Goette, L., Groshen, E. L., and Holden, S. (2007a). How Wages Change: Micro Evidence from the International Wage Flexibility Project. *Journal of Economic Perspectives*, 21(2):195–214.
- Dickens, W., Goette, L., Groshen, E. L., and Holden, S. (2007b). The interaction of labor markets and inflation: Analysis of micro data from the International Wage Flexibility project. *mimeo, Brookings Institution*, pages 1–51.
- Du Caju, P., Fuss, C., and Winttr, L. (2007). Downward Wage Rigidity for Different Workers and Firms: an evaluation for Belgium using the IWFP procedure. *ECB Working Paper*, 840.
- Fuss, C. (2009). What is the most flexible component of wage bill adjustment? Evidence from Belgium. *Labour Economics*, 16(3):320–329.
- Goette, L., Sunde, U., and Bauer, T. (2007). Wage Rigidity: Measurement, Causes and Consequences. *The Economic Journal*, 117(524):F499–F507.
- Gottschalk, P. (2005). Downward nominal-wage flexibility: real or measurement error? *Review of Economics and Statistics*, pages 556–568.
- Kahn, S. (1997). Evidence of nominal wage stickiness from microdata. *The American Economic Review*, 87(5):993–1008.
- Kátay, G. (2011). Downward wage rigidity in Hungary. *ECB Working Paper*, 1372.
- Lunnemann, P. and Winttr, L. (2010). Downward wage rigidity and automatic wage indexation: Evidence from monthly micro wage data. *ECB Working Paper*, 1269.
- Messina, J., Duarte, C., Izquierdo, M., Du Caju, P., and Hansen, N. (2010). The Incidence of Nominal and Real Wage Rigidity: An individual-based sectoral approach. *Journal of the European Economic Association*, 8(May 2010):487–496.
- OECD (2014). Sharing the pain equally ? Wage adjustments during the crisis and recovery. In *OECD Employment Outlook 2014*. OECD Publishing.
- Sociaal-economische Raad (2013). Verbreiding draagvlak cao-afspraken.