Downward Nominal and Real Wage Rigidity in the Netherlands

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Abstract

During the Great Recession companies were confronted with decreasing demand. One possible strategy to survive instead of cutting down employment, could be to reduce wages. However, it is well known that workers may tend to be reluctant to accept nominal or real wage cuts. In this thesis the amount of downward wage rigidity in the Netherlands is studied. Although substantial research has been performed in recent years, accurate estimates for the Netherlands are currently not available. All previous studies for The Netherlands are outdated (the most recent data is up till 2001) or use survey or aggregated data, while wage rigidity is best studied using administrative data on individual wages to avoid measurement error and the masking of wage cuts of one group of workers by wage increases of others. In this thesis wage rigidity is estimated using administrative data at the individual level.

The most notorious problem in estimating wage rigidity is measurement error. Measurement error will lead to spurious (and sometimes negative) wage changes, which could lead to an underestimate of the amount of rigidity. Therefore three methods are used, two of which correct for measurement error. These are the three main approaches well known from the literature that have been developed especially to measure wage rigidity. Also the use of administrative data helps to limit measurement error. Besides presenting up to date estimates of wage rigidity for the Netherlands, this thesis also analyses the determinants of wage rigidity and offers a comparison between three main approaches for estimating wage rigidity. The results of the three methods are found to differ substantially. Estimates for the fraction of wages covered by real wage rigidity range from 10 % up to 67 %. The results of the preferred model-based IWFP method indicate that the amount of real and nominal wage rigidity is about average compared to other countries. Furthermore, my analysis of the determinants of Dutch wage rigidity shows that the presence of wage rigidity is unevenly distributed among groups of workers. I find 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 experienced zero or positive employment growth in the previous year. Furthermore I find that large companies have less nominal wage rigidity than small and middle-sized companies, while showing more real wage rigidity. In addition, people with a higher wage show a higher degree of real wage rigidity. I have indications that people working in a shrinking sector province combination are to some extend willing to accept real wage cuts in favor of employment. I also find that the amount of real wage rigidity decreases and nominal rigidity increases in a low inflation environment.

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Chapter 1

Introduction

In July 2013 the Dutch unemployment rate was at the highest point since 1996: 8.7 %. If competitive labor market theories hold, real wages should decline and involuntary unemployment should disappear, since with a lower real wage firms are willing to hire more workers. In the low-inflation environment of the past years, with inflation rates between 1.1 and 2.5 %, real wage cuts (a wage increase below the inflation) might even result in nominal wage cuts (a wage change of less than zero percent). But do nominal wage cuts occur in practice? On the one hand, there seems to be a taboo on nominal wage cuts: the proposal by Capgemini in January 2013 to cut nominal wages led to upset worker unions and a large public debate about nominal wage cuts. On the other hand, the Netherlands is famous for wage moderation agreements ("loonmatigingsakkoorden") concluded by social partners. That might indicate that adjusting real wages downward is not a big problem. In this thesis I study the prevalence of downward wage rigidity in the Netherlands: in how far do wages decline when labor demand decreases?

Wage rigidity might cause involuntary unemployment. If workers are willing to work for a particular real wage, but cannot find employment, this can be characterized as involuntary unemployment. The solution seems simple: decreasing the real wage will lead to an increasing labor demand, and a decreasing supply. This will eliminate involuntary unemployment. However, if wage rigidity is present, adjustment of the wage downwards is not possible and therefore involuntary unemployment will remain. Essentially this leads to conflicting interests between insiders and outsiders: insiders want to get the highest possible wage change, while outsiders benefit from increasing labor demand.

The degree of wage rigidity is also an important determinant of economic policy. If nominal wages are downwardly rigid the 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 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.

Recent studies all use micro-data to estimate the degree of wage rigidity. A common definition for the extent of wage rigidity is the fraction of workers reluctant to wage cuts (either real or nominal). I will call this the fraction of workers covered by wage rigidity (sometimes called probability of being covered by wage rigidity). If a worker is covered by real or nominal wage rigidity, he receives a higher wage change than he would receive in case of fully flexible wages. In order to measure the extent of wage rigidity one would like to compare the wage changes under a regime of wage rigidity and under a regime of fully flexible wages. This is however not possible since both regimes do not exist in reality at the same time. Therefore, the observed regime is compared with a statistical construction that represents the regime of fully flexible wages. The latter is called the 'notional distribution' and reflects the distribution of wage changes under a (hypothetical) regime of fully flexible wages. The extent of wage rigidity is then obtained, in essence, by comparing the actual and the notional distribution. If a worker is covered by real or nominal wage rigidity, he will receive a real or nominal wage freeze if he would have received a wage change below a certain threshold in absence of wage rigidity. This threshold is zero in case of nominal rigidity (a worker does not agree with a wage cut) and in general the inflation expectation in case of real rigidity. This threshold is not equal to the true inflation, since it is assumed that employees and employers look forward when determining wage changes. Workers who get a wage increase (far) above the threshold can still be "reluctant to wage cuts" although this information is not observed. 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 and therefore all methods require some assumptions on this notional distribution. These methods use as starting point that a part of the wage changes that would have been located below the threshold if there was no rigidity, are instead located at the threshold. It is assumed that the nominal rigidity threshold is the same for every individual. The real rigidity threshold, normally the inflation expectation, is assumed heterogeneous, instead. This follows from the fact that the inflation expectations differ among workers. In the literature, the inflation expectation is almost always modeled symmetrically. These methods are in fact looking for a heap of observations around or at a threshold and missing observations in the part below the threshold.

A condition for deriving policy implications is an accurate estimate of wage rigidity in the Netherlands. Although substantial research has been performed in recent years, accurate estimates for the Netherlands are currently not available. Estimates are outdated (the most recent data is up to 2001) and furthermore all previous studies for the Netherlands use survey data or aggregated data, while wage rigidity is best studied using administrative data on individual wages to avoid measurement error and the masking of wage cuts of one group of workers by wage increases of others. There is no estimate of wage rigidity available using administrative data at the individual level. This motivates my research. I expect to find a low amount of real wage rigidity, since the Netherlands is famous for its wage moderation agreements ('loonmatigingsakkoorden'). In wage moderation agreements it is agreed that contractual wages will not rise more than a certain determined percentage. Often this is lower that the inflation expectation. Nominal wage cuts, however, led to a heated debate. Therefore I expect to find a high amount of nominal rigidity.

The most notorious problem in estimating wage rigidity is measurement error. Measurement error will lead to spurious (and sometimes negative) wage changes, which could lead to an underestimate of the amount of rigidity. The main advantage of my data is that it is from an administrative source. Data from the Social Statistical files (SSB), obtained from Statistics Netherlands, for 2006-2012 is used. In this data set monthly wage information is available for all jobs in the Netherlands. In general, the amount of measurement error in administrative data is much smaller compared to survey data. This is a clear advantage of the data used. To address the issue of measurement error in estimating wage rigidity various methods have been developed. All these methods are specifically developed to measure wage rigidity. As said before, all methods assume that part of the wage changes that would have been located below the threshold if there was no rigidity, are instead located *at* the threshold. In this research I will use three main approaches to measure wage rigidity. I have chosen to use these methods since they are the de facto standard methods for estimating wage rigidity and specifically developed for this purpose and therefore applicable. This makes my estimates comparable to estimates of other countries. First a simple approach is used, which measures wage rigidity by dividing the number of wage freezes by the number of wage cuts as described in Dickens et al. (2007a). This method is developed by the researchers of the International Wage Flexibility Project as an easy way to estimate the degree of wage rigidity in a country. In this method the absence of measurement error is assumed. Second, a two-stage Method of Moments estimator is used, which is also developed for the International Wage Flexibility Project as described in Dickens et al. (2007b). The IWFP has developed this protocol in order to make estimates of wage rigidity comparable with each other. This method makes a measurement error correction based on the autocorrelation of wage changes. Lastly, wage rigidity is examined using a model which takes into account normally distributed measurement error. Also this model is specifically developed for measuring wage rigidity. The model is estimated using a Maximum Likelihood method as discussed in Goette et al. (2007). As an additional analysis I will study the determinants of wage rigidity using a fractional logit model, where the probability of real or nominal wage rigidity is the dependent variable and individual or firm characteristics are used as independent variables. My contribution to the existing literature consists of up to date estimates of wage rigidity in the Netherlands, an analysis of the determinants of Dutch wage rigidity and a comparison between three main approaches for estimating wage rigidity.

The results are found to differ substantially over the three methods. Estimates of real wage rigidity range from 10 % up to 67 %. The results of the model-based IWFP method indicate that the amount of real and nominal wage rigidity is about average compared to other countries, with 24 % and 39 % respectively. Furthermore I find that large companies have less nominal wage rigidity than small and middle-sized companies, while showing more real wage rigidity. Older workers have a higher amount of real and nominal wage rigidity. Also people with a higher wage have a higher degree of real wage rigidity. I have indications that people working in a shrinking sector province combination are to some extend willing to accept real wage cuts in favor of employment. I also find that the amount of real wage rigidity decreases and nominal rigidity increases in a low inflation environment.

The rest of this thesis is organized as follows: In Chapter 2 I discuss the literature on wage rigidity. Chapter 3 explicates the wage rigidity estimation procedures and methodologies for explaining wage rigidity outcomes. Chapter 4 discusses the data, including the measure for wages and the explanatory variables that are used. Chapter 5 presents the results and Chapter 6 concludes.

Chapter 2

Literature

This chapter gives an overview of the current state of knowledge about wage rigidity in general and in the Netherlands in particular. Section 2.1 starts by discussing the types of wage rigidity that exist and the main theories explaining downward wage rigidity, while Section 2.2 discusses methods used to measure wage rigidity. Lastly, the Dutch labor market and wage rigidity in the Netherlands are discussed in Section 2.3.

2.1 Theoretical literature

In the literature two types of wage rigidities are distinguished: symmetric rigidities and asymmetric rigidities. Two types of symmetric rigidities can be distinguished. A first source of symmetric wage rigidity stems from the fact that wages adjust infrequently and with some delay to shocks. Taylor (1999) discusses the relevant literature and models concerning this type of wage rigidity in detail. More recently, Heckel et al. (2008) studied this type of wage stickiness using micro-economic data. They conclude that both forward and backward-lookingness drives wage changes: wages depend on future and past inflation rates. Furthermore they find that predetermination is a relevant feature of wage changes. Predetermination means that wage changes happen more frequently than wage decisions. For example an employer and a union agree in 2012 on a wage increase of 1 % in 2012 and 1 % in 2013. Another source of symmetric wage rigidity are so called menu costs. Employers do not adjust wages if the wage adjustments are small, to save administrative costs of changing the salary. These are often called menu costs, because of the similarity with restaurants who do not make small adjustments to their prices because of the costs of changing the menu (Sheshinski and Weiss, 1977). Symmetric wage rigidities are beyond the scope of this thesis, which focuses on how wages respond in a phase of declining demand.

Asymmetric rigidities can be classified into two types: Downward Nominal Wage Rigidity (DNWR) and Downward Real Wage Rigidity (DRWR). Downward Nominal Wage Rigidity is due to the fact that employees are reluctant to nominal wage cuts. This is illustrated by Kahneman et al. (1986), who ask respondents if it is fair if an employer lowers wages by 7 % when there is no inflation, while asking other respondents what they think of increasing wages by only 5 % when there is 12 % inflation. In the first case 62 % of the respondents thinks this is unfair, while in the second case this is only 22 %. This is called money illusion. Downward Real Wage Rigidity occurs if employees want to maintain their purchasing power and therefore are reluctant to accept real wage cuts. In some countries automatic wage indexation takes place to prevent losses in purchasing power. Lunnemann and Wintr (2010) study the effects of automatic wage indexation on real wage rigidity for Luxembourg and find that real wage rigidity is related to wage indexation, but that additional factors are required to explain *downward* real wage rigidity.

Besides the reluctancy of workers to accept wage drops, three main theories explain wage rigidity (or in some cases, wages above the market clearing level) from the employer side: *implicit contract theories*, *efficiency wage theories* and *insider-outsider theories.* Two main implicit contract theories exists. First, Azariadis (1975) states that risk neutral employers agree to pay stable wages to 'insure' employees from wage fluctuations . In exchange, employers are allowed to pay a lower wage. These stable wages are a form of wage rigidity. Second, Lazear (1979) connects wages to the Value of the worker's Marginal Product (VMP) and states that "it pays both parties to agree to a long-term wage stream which pays workers less than their VMPs when young and more than the VMPs when old."

In efficiency wage theories it is assumed that managers have, for various reasons, an incentive to pay higher wages than the market clearing level. The most well-known theory for paying efficiency wages is to avoid shirking (Shapiro and Stiglitz, 1984). When it is difficult to monitor the quality and/or quantity of the work of employees, paying a higher wage will increase the cost of a job loss for the employee, which could be effective in preventing a worker from shirking. The fact that productivity depends positively on wages can be a reason to not cut wages.

In insider-outsider theories, as first developed by Lindbeck and Snower (1986), it is assumed that it is costly to exchange a firm's full-fledged employees (insiders) for unemployed workers (outsiders). Insiders can use this in the process of negotiation to get paid higher wages or to resist wage cuts. In Lindbeck and Snower (2001) a more recent overview is given of the insider-outsider literature.

2.2 Empirical literature

In the 90s research on wage rigidity based-on micro-data started. McLaughlin (1994) can be seen as one of the pioneers who investigated both nominal and real wage rigidity. Until the mid 90s the general opinion was "the existence of wage stickiness is not in doubt". McLaughlin states that perhaps it should be. He finds that both nominal and real wage cuts occur frequently in the United States (17.3 % and 42.9 % respectively). Furthermore he examines the variance of wage growth and finds that this does not support implicit-contract models.

Kahn (1997) uses a different approach for estimating nominal wage rigidity using the same data set as McLaughlin (1994) did. He tests the assumption that (in the absence of rigidity) the percentage of observations in a cell of a histogram at a certain distance from the median is equal over time. He rejects this hypothesis for wage earners and conclude that there is "evidence for substantial stickiness of nominal wages for wage earners". He further criticizes the method used by McLaughlin.

Card and Hyslop (1997) assume that the wage change distribution is symmetric around the median. They calculate a counterfactual bottom half using the upper half and conclude that there is evidence for downward nominal rigidities. Akerlof et al. (1996) criticizes the research of both Card and Hyslop (1997) and Kahn (1997) since they assume the absence of measurement error. Akerlof et al. (1996) shows that most negative wage changes are due to measurement error. Altonji and Devereux (2000) agree with this criticism and develop a model which incorporates measurement error in which a "flexible wage model, a downwardly rigid wage model, and a model that allows for nominal cuts in certain circumstances" are nested. Furthermore employee characteristics are used to construct a counterfactual distribution. They "overwhelmingly" reject the hypothesis of perfect flexibility. However they also reject the hypothesis of perfect downward nominal rigidity. The criticism regarding all of the above mentioned studies is directed against the fact that they use data in a period with very high inflation, while in a low inflation environment nominal wage cuts would not be seen as unusual (Akerlof et al., 1996, Comments and Discussions (pages 60-66)). Fehr and Goette (2005) adapt the model of Altonji and Devereux (2000) by allowing heterogeneity. Data of Switzerland between 1991 and 1997 is used; in those years the inflation was low. The researchers indicate significant nominal wage rigidity even in the low inflation environment. Goette et al. (2007) build a model which takes into account both downward nominal and downward real wage rigidity in combination with normally distributed measurement errors. Empirical research using this model finds a high degree of real wage rigidity for all three countries (the UK (Barwell and Schweitzer, 2007), Italy (Devicienti et al., 2007) and Germany (Bauer et al., 2007)), but not much evidence for downward nominal wage rigidity.

Instead of incorporating measurement error in the model, it is also possible to correct the distribution for it. Often this correction is based on the property that measurement errors cause negative autocorrelation in the wage changes. 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 $t+1$. Gottschalk (2005) uses structural break tests on monthly wage data to indicate legitimate wage changes. The advantage of this method is that relative weak identifying assumptions are used.

The most recent research on estimating DNWR and DRWR is based on the approach of the International Wage Flexibility Project (IWFP). The IWFP is a consortium of 40 researchers who study the costs and benefits of inflation using micro-data for 16 countries. The IWFP distinguishes two estimates of wage rigidity: simple measures and model-based measures. The starting point for both methods is the distribution of year to year wage changes, either for all workers or for specific groups. The simple measures are based on dividing the number of nominal wage freezes by the number of nominal wage cuts and wage freezes and a similar measure for DRWR. This method is discussed in more detail in Dickens et al. (2007a). This method does not correct for measurement error. The IWFP has also developed a model-based approach which corrects the distribution for measurement errors and estimates rigidity using a two-stage Method of Moments approach. The method and its results are described in general Dickens et al. (2007b), while the technical details of the approach are discussed in Dickens and Goette (2005). In the first step, the wage change histogram is corrected using autocorrelation measures. In the second step wage rigidity is identified. For the first step it is assumed that measurement errors have a two-sided Weibull distribution. Using this assumption and the autocorrelation of wage changes, it is possible to compute the fraction of observations for each cell in the histogram that should be located in another cell. Using this information the true wage change distribution is estimated. By comparing the true distribution with the notional distribution, the distribution that would hold in absence of wage rigidity, rigidity can be measured. Rigidity is measured by minimizing the distance between the expected moment conditions and their empirical counterparts.

Lunnemann and Wintr (2010) find that the IWFP procedure is robust and that the results of the correction methods of Gottschalk (2005) and Dickens and Goette (2005) do not differ much. In Dickens et al. (2007b) model-based estimates are given for Austria, Belgium, Denmark, Finland, France, Germany, Italy, Norway, Portugal, Sweden and Switzerland using data from administrative sources from the 70s till 2000 (ranges differ across countries). Also estimates using survey data from the UK, the US, Greece, Ireland and the Netherlands from 1993 till 2001 (for most countries) are presented. Later Lunnemann and Wintr (2010) present estimates using this procedure for Luxembourg and Kátay (2011) for Hungary. Duarte (2008) and Du Caju et al. (2007) present additional results for Portugal and Belgium respectively, using more recent data than used in Dickens et al. (2007b).

2.3 The Netherlands

In the Netherlands a large part of decisionmaking concerning the labor market takes place in the Labour Foundation (Stichting van de Arbeid). The Labour Foundation consists of the "social partners" i.e. representatives of the three main trade unions and main employers' associations. Sometimes their considerations result in statements concerning courses of action for the employers' associations and trade unions that negotiate collective bargaining agreements. In 1982 the

Wassenaar Agreement (Akkoord van Wassenaar) was settled in which both parties agreed on moderation of wages ("loonmatiging"). Since then, in economic crises the Labour Foundation often came to an agreement on wage moderations. In 1993 'Een nieuwe koers', in 2003 'Het najaarsakkoord' and in 2009 'Het loonmatigingsakkoord'. These agreements could be an indication of low wage rigidities. Furthermore De Beer (2013) shows that real contractual wages did not increase over the past 36 years. The earned real wages however have increased by 25 % due to incidental wage changes. De Nederlandse Bank (2014) shows that during the recent crisis the real contractual wage changes have been negative since 2010. This suggests that downward real wage rigidity is low in the Netherlands. In the Netherlands 83.2 % of the employees is covered by a collective bargaining agreement (OECD, 2012), which is high in comparison to other countries. It is possible for the Minister of Social Affairs and Employment to declare the collective bargaining agreement universally binding.

Researchers have used various methods for estimating wage rigidity in the Netherlands. Layard et al. (1991) give estimates of real wage rigidity (0.25), defined as "the extent to which wage pressure is converted into unemployment at constant inflation" and nominal wage rigidity (0.24), which is defined as "the long-run inflation-unemployment trade-off". The estimates for the Netherlands are about average compared to other OECD countries. However the approach of Layard et al. (1991) is widely criticized[1].

Holden and Wulfsberg (2007a) research Dutch DNWR. They calculate the fraction of wage cuts prevented by comparing the empirical distribution with a notional distribution, constructed using interquartile ranges. They estimate the fraction of wage cuts prevented at 0.387, which is about average compared to other western countries. They reject the hypothesis of no DNWR for the Netherlands using a statistical test. These estimates are based on an unbalanced panel of industry-level data for the annual percentage growth of gross hourly earnings for manual workers from Eurostat for 1973-1999. In Holden and Wulfsberg (2007b) they also investigate DRWR using a similar approach and the same data. In this study they estimate the fraction of real wage cuts prevented at $0.033\,(\pm 0.251)$. This result, however, is not significant. The result is about average compared to other countries. Next to real wage rigidity at zero, they also consider rigidity at –2 and –5 percent, with estimates $0.167\,(\pm 0.041)$ and $0.533\,(\pm 0.103)$ respectively. Both estimates are significant. Note, however that these estimates can interfere with nominal wage rigidity if the inflation is below 2 or 5 percentage points respectively.

Dickens et al. (2007a) present the results of (a part of) the International Wage Flexibility Project. A simple measure is used for calculating the fraction of people effected by DNWR and DRWR. The fraction of workers covered with DNWR is estimated at 30 % for the Netherlands, which is about average relative to other countries. The estimate of DRWR is around 1 %, which is the lowest compared to all other countries. The model-based estimates of DNWR and DRWR are presented in Dickens et al. (2007b). Here a DRWR of about 10 % was found and a DNWR of 30 %. These estimates (for the Netherlands) are based on the European Community Household Panel for 1993-2001.

[1] See for example: Berthold et al. (1999)

Chapter 3

Methodology

As discussed in Section 2.2 various approaches have been developed to measure wage rigidity. In the past years the IWFP methodology has become the international standard for estimating wage rigidity. The International Wage Flexibility Project uses two methods to asses the extent of DRWR and DNWR. A model-based approach (Dickens et al., 2007b) and a simple approach (Dickens et al., 2007a). 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."

First I will apply the simple IWFP methodology from (Dickens et al., 2007a) to Dutch administrative data. This is discussed in as discussed in Section 3.1. Then I will extend this analysis by estimating wage rigidity using the model-based IWFP methodology (Dickens et al., 2007b), which is explained in Section 3.2. Various estimates for other countries are available for both methods, which makes it possible to compare the results internationally. Finally, I will apply the Maximum Likelihood method of Goette et al. (2007). This method is discussed in Section 3.3. All three methods focus on wage rigidity among job stayers, i.e. workers that work for the same firm as the year before.

These are the three main approaches well known from the literature that have been developed especially to measure wage rigidity. The literature on wage rigidity agrees on the definition and the main model of wage rigidity. All three methods are trying to measure this quantity and model wage rigidity in the same way: the fraction of workers reluctant to wage cuts (either real or nominal), also called the fraction of workers covered by wage rigidity. These methods assume that a part of the population of job stayers cannot agree with a real or nominal wage cut. If an employer would propose a wage cut, the employer and employee will not come to an agreement. Instead, they will or agree on a (real or nominal) wage freeze. These methods assume that a fraction of the wage changes that would have been located below the threshold if there was no rigidity, are instead located at the threshold. It is assumed that the nominal rigidity threshold is the same for every individual. The real rigidity threshold, normally the inflation expectation, is assumed heterogeneous, instead. This follows from the fact that the inflation expectations differ among workers. In the literature, the inflation expectation is almost always modeled symmetrically (often normally). These methods are in fact looking for a heap of observations around or at a threshold and missing observations in the part below the threshold. This approach tries to estimate the extent of wage rigidity by inspecting the difference between the observed wage changes and what we think the wage changes would have been in absence of rigidity. I do not observe what the wage changes would have been, therefore some assumptions are required. The methods use different assumptions on how the wage changes would have looked like in absence of rigidity (See Section 3.4). All methods, however, agree on the fact that the distributions are 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 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 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 by the researchers of the International Wage Flexibility Project 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. Furthermore estimates for various countries are already available using this method. The disadvantage, however is that this method does not take measurement error into account. Measurement error causes spurious (and sometimes negative) wage changes (a sign of flexibility), which leads to an underestimation of the amount of rigidity. The researchers of the IWFP decided to develop another method to measure rigidity to overcome this problem. The researchers wanted to develop one standard protocol, which would make all estimates completely comparable. 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 a wage, lead to autocorrelation in the wage changes: e.g. if you report accidentally a high wage this will cause a wage increase first, and later a wage decrease (autocorrelation). After this correction is made, the method estimates wage rigidity by comparing the observed distribution with a notional distribution that is assumed two-sided Weibull. Goette et al. (2007) did also want to take into account measurement error, but experienced the model-based IWFP method as 'too complex', but agreed on the fact that measurement error should be taken into account. Therefore they developed a model that incorporates measurement error, but uses a well-known methodology: the Maximum Likelihood method. This method uses, as do the other methods, the same main model for estimating wage rigidity: that a fraction of the wage changes that would have been located below the threshold if there was no rigidity, are instead located at the 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 to facilitate the approach.

3.1 The simple IWFP method

The simple IWFP method is based on asymmetries in the wage change histogram. 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:

$$p^c_{N,t} = \frac{f_{n,t}}{f_{n,t} + c_{n,t}}, \tag{3.1}$$

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 is important as you will see later. To indicate that this probability is conditional on not being covered by DRWR, I have added a c-superscript.

For DRWR a similar measure is used:

$$p_{R,t} = \frac{f_{r,t}}{f_{r,t} + c_{r,t}}, \tag{3.2}$$

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 that 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 λ_t below the (mean) inflation expectation π_t from the symmetric counterpart υ_t (the fraction of observations above $M_t + (M_t - \pi_t)$, where M_t is the median of the wage change distribution in year t (see Figure 3.1)). 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 ($f_{r,t} = 2(\upsilon_t - \lambda_t)$). 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, I take $f_{r,t} + c_{r,t} = \upsilon_t$. This gives:

$$p_{R,t} = \frac{f_{r,t}}{f_{r,t} + c_{r,t}} = \frac{2(\upsilon_t - \lambda_t)}{\upsilon_t}. \tag{3.3}$$

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.

3.2 The model-based IWFP method

In this section I will discuss the intuition behind the model-based IWFP method. This section is based on the technical derivations of the IWFP method as formulated in Dickens and Goette (2005). The technical derivations for the error-correction step are discussed in detail in Appendix A[1].

The model-based IWFP method consists of two steps. The first step is the error correction step. This step is discussed in Section 3.2.1. The second step is the estimation step, which is discussed in Section 3.2.2. Both steps use the Method of Moments.

3.2.1 Correcting the wage change distribution

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

[1]To be clear: Those derivations are included and explained for completeness and do not contain new material.

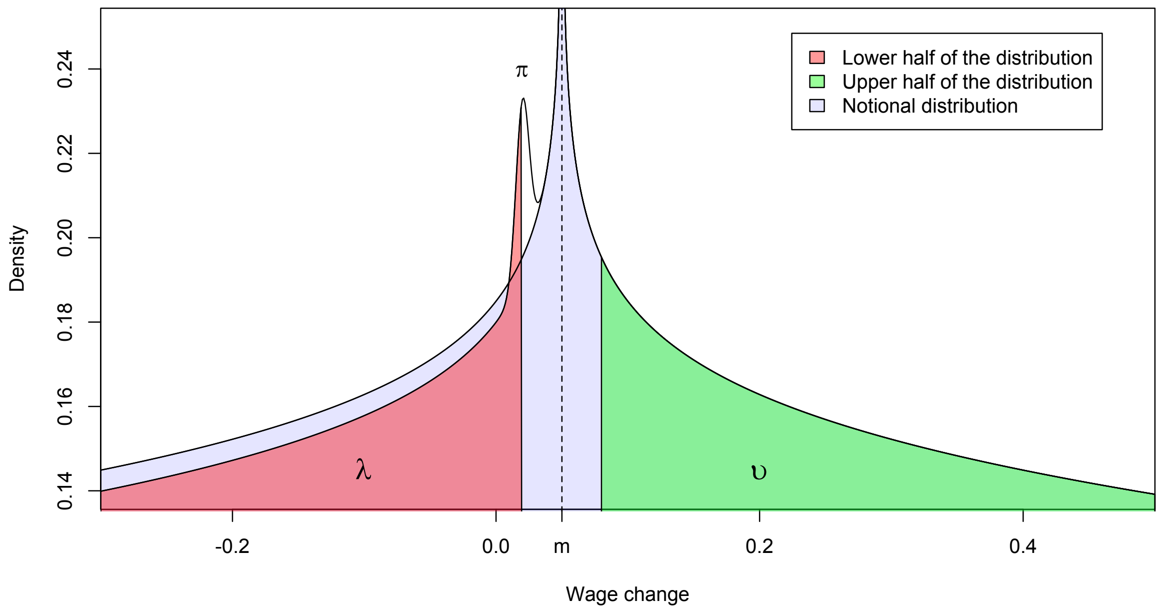


Figure 3.1: The probability distribution of the observed and notional wage changes

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.

The model-based IWFP method tries to correct the observed histogram for measurement error and measures wage rigidity on the basis of a 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). 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. So, using this information the corrected distribution can be calculated, and subsequently wage rigidity can be measured.

It is important to make a distinction between monthly and annual earnings: this is due to the fact that wage changes take place across the year. This means that for example a wage change in June 2012 will cause a change in annual earnings in both 2012 and 2013. The IWFP procedure is able to correct the histograms for both types of wages, but use a different approach. In the empirical analyses I will only consider monthly wages.

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

$$\mathbf{m}_t = \mathbf{R}_t^{-1}\mathbf{m}_t^o. \tag{3.4}$$

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[2]. 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. For a full description of the variables used in the model-based IWFP procedure, see Appendix A. To find those parameters, moment conditions are derived for the fraction of switchers. This is where the autocorrelation comes in.

A switcher is defined as someone who had a wage change $d^o_{i,t} > U_{t,q}$ and in the consecutive year $d^o_{i,t+1} < L_{t,q}$ or where $d^o_{i,t} < U_{t,q}$ and $d^o_{i,t+1} > L_{t,q}$. 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. I 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}, $p_{m|e}$[3]. To reduce the number of parameters, b_t is calculated as a function of the estimated auto-covariance $\sigma_{d_t,d_{t+1}}$. This leaves only a, p_{ne}, $p_{m|e}$ left to be optimized by minimizing the weighted distance between the theoretical and empirical moment conditions. Both matrices $\mathbf{R}_t$ and $\mathbf{S}_t$ (the matrix that is required to calculate the theoretical fraction of switchers) use multiple-dimensional integrals of the two-sided Weibull distribution. Since no analytical expressions are known for these integrals, I approximate them using Monte-Carlo integration. Here, I deviate from the methodology as defined by the original IWFP procedure, where Gauss-Legendre quadrature is used. I do this, since discontinuities at zero caused severe approximation problems. I use Powell's method to optimize for the parameters a, p_{ne}, $p_{m|e}$, since the approximation of the integrals leads to discontinuities in the derivatives and Powell's method is derivative-free.

3.2.2 Measuring wage rigidity

Once the for measurement error corrected histogram $\mathbf{m}_t$ is obtained, the amount of wage rigidity can be estimated. This 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 I try to fit the expected histogram, given the parameters, to the corrected histogram. Using this approach I am able to find the appropriate parameters especially with respect to the fraction of observations covered by wage rigidity. I do not use the individual observations for this step, since in the error correction step I have corrected the heights of the cells of the histogram and have not corrected individual observations. Therefore I do not have information on the corrected wage change of every individual observation. The expected histogram is based on the model that wage changes come from a two-sided Weibull distribution (the notional). 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 fall below zero will receive a (nominal) wage freeze instead. Using this model, and the parameters that have to be found, I am able to 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 expected distribution is calculated according to the following model. The notional wage change $d^n_{i,t}$ is modeled as a draw from a two-sided Weibull-distribution. Now the real adjusted

[2]See Equation A.4
[3]See Equation A.9

wage change can be derived as $d^r_{i,t}$

$$d^r_{i,t} = \begin{cases} d^n_{i,t} & \text{if } \epsilon^r_{i,t} > p_{R,t} \\ \max(\pi_{i,t}, d^n_{i,t}) & \text{otherwise} \end{cases}. \tag{3.5}$$

where $\pi_{i,t}$ is the inflation expectation (modeled as a normally distributed variable with mean π_t and variance $\sigma^2_{\pi,t}$), $\epsilon^r_{i,t}$ 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

$$d_{i,t} = \begin{cases} 0 & \text{if } d^r_{i,t} \leq 0 \text{ and } \epsilon^n_{i,t} < p^c_{N,t}) \text{ or } (-.01 \leq d^r_{i,t} \leq .01 \text{ and } \epsilon^1_{i,t} < p_{s_1,t}) \\ & \text{or } (-.02 \leq d^r_{i,t} < -.01 \text{ or } .01 < d^r_{i,t} \leq .02 \text{ and } \epsilon^2_{i,t} < p_{s_2,t}) \\ d^r_{i,t} & \text{otherwise} \end{cases}, \tag{3.6}$$

where $\epsilon^n_{i,t}, \epsilon^1_{i,t}$ and $\epsilon^2_{i,t}$, are all uniform distributed random variables with support on the unit interval, $p^c_{N,t}$ is the probability of being subject to downward nominal rigidity and 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 %.

Similar to the simple IWFP method, the probability of being covered by DNWR is defined 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 here the estimate of DNWR is the probability of being covered by DNWR, conditional on not being covered by DRWR.

This model easily leads us to the following moment conditions for the for measurement error corrected histogram $\mathbf{m}_t$ and its individual elements $m_{j,t}$.

$$m_{j,t} = E[m_{j,t}] = \begin{cases} j < -2 & (1 - p_{N,t})z_{j,t} \\ j = -2 & (1 - p_{s_2,t})(1 - p^c_{N,t})z_{j,t} \\ j = 1 & (1 - p_{s_1,t})(1 - p^c_{N,t})z_{j,t} \\ \text{j=0} & \begin{array}{c} p_{s_2,t}z^n_{2,t} + p_{s_1,t}z_{1,t} + (p_{s_1,t} + p^c_{N,t} - p^c_{N,t}p_{s_1,t})z_{-1,t} \\ +(p_{s_2,t} + p^c_{N,t} - p^c_{N,t}p_{s_2,t})z_{-2,t} + p^c_{N,t}\sum_{k=-100}^{-3} z_{k,t} \end{array} \\ j = 1 & (1 - p_{s_1,t})z_{j,t} \\ j = 2 & (1 - p_{s_2,t})z_{j,t} \\ j > 2 & z_{j,t} \end{cases}, \tag{3.7}$$

where the fraction of notional real adjusted wages that would fall in cell j of the histogram $z_{j,t}$ is given by

$$z_{j,t} = (1 - p_{R,t} + p_{R,t}\Phi_t(l_j))\,(F_t(u_j) - F_t(l_j)) + p_{R,t}\,(\Phi_t(u_j) - \Phi_t(l_j))\,F_t(u_j). \tag{3.8}$$

Here $F_t(x)$ is the cumulative wage change distribution for the two-sided Weibull and $\Phi_t(x)$ is the cumulative normal distribution with mean π_t and variance $\sigma^2_{\pi,t}$. In fact these moments can be seen as the expected histogram. Now the distance between the empirical moments and the theoretical moments can be minimized. This can be seen as fitting the histogram.

3.3 The Maximum Likelihood method

The third method that I will explore is the Maximum Likelihood method, as documented in Goette et al. (2007). This method is based on the assumption that measurement errors are normally distributed. The same assumption is made for wage changes. Although this does clearly not reflect reality (notably Goette himself states in Dickens et al. (2007a) that "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"), I will use this method to see if this still leads to the same outcomes.

The method of Goette et al. 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. Goette et al. assume that wage changes are generated according to a linear combination of covariates and a normally distributed error term with variance $\sigma^2_{\omega,t}$

$$d^n_{i,t} = \mathbf{x}_{i,t}\beta + \omega_{i,t}, \tag{3.9}$$

where $\mathbf{x}_{i,t}$ are covariates $d^n_{i,t}$ is the notional wage change and β the parameter vector. I will use gender, age, company size, part-time employment[4] and year- and sector-dummies as covariates. Now in the nominal rigidity regime wage changes $d^n_{i,t}$ below zero are not allowed and wages will be set to zero according to:

$$d_{i,t} = \begin{cases} d^n_{i,t} & \text{if } d^n_{i,t} \geq 0 \\ 0 & \text{if } d^n_{i,t} < 0 \end{cases}. \tag{3.10}$$

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[5]:

$$d_{i,t} = \begin{cases} d^n_{i,t} & \text{if } d^n_{i,t} \geq \pi_{i,t} \\ \pi_{i,t} & \text{if } d^n_{i,t} < \pi_{i,t} \end{cases}. \tag{3.11}$$

The cutoff $\pi_{i,t}$ below which the wage change becomes rigid is modeled as heterogeneous, since inflation expectations may differ over the year and per individual. $\pi_{i,t}$ is modeled as normally distributed with mean π_t and variance σ^2_π. 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 $d^o_{i,t}$ is assumed to be corrupted by measurement error. Goette et al. their method assumes that errors are normally distributed with mean 0 and variance σ^2_m 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^2_m). This leads to a total of 15 regimes, which are shown in Table 3.1.

Table 3.1: 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

[4]The Netherlands has the highest percentage of part-time workers. According to Eurostat 50 % of the employees works part-time

[5]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

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). I have implemented this likelihood function, after applying a correction since the likelihood function appeared to be incomplete. The Technical Appendix states that the likelihood contribution of a constrained observation in the nominal rigidity regime making one error P_{NC1} is given by $\frac{1}{\sigma_m}\phi\left(\frac{\Delta w_i^o}{\sigma_m}\right)$. This, however should be $P_{NC1} = \frac{1}{\sigma_m}\phi\left(\frac{\Delta w_i^o}{\sigma_m}\right) \cdot \Phi\left(\frac{0-X_i\alpha}{\sigma_w}\right)$, since the likelihood of being constrained should also be taken into account. A similar expression can be derived for P_{NC2}, P_{RC1} and P_{RC2}. 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 π_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 π_t are year-dependent.

3.4 Method comparison

Hence, all three methods model wage rigidity in the same way, but use completely different approaches and assumptions, especially on the notional and error distribution. The most important differences are summarized in Table 3.2. 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 it is known that measurement errors are present, even in administrative data, this is a weakness of this method. On the other hand, the simple IWFP method uses the least restrictive assumptions on the notional distribution (the distribution in absence of rigidity).

Table 3.2: 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

The simple IWFP method is based on the assumption that the wage change distribution, in absence of rigidity, is symmetric around the median. This assumption is made in the model-based IWFP method and the Maximum Likelihood method as well, since they both assume a particular symmetric distribution. Testing this assumption 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[6], we believe that symmetry is a natural starting

[6]Verbeek: The assumption that the notional distribution is symmetric

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. 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. No arguments are given in Goette et al. (2007) for assuming a normal distribution, while Dickens et al. (2007a) give some 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, but no motivation for this particular choice is given. 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 drawbacks. I 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 my large sample size (26,601,768 observations) this is not feasible. In an ideal situation I would propose to identify two-sided Weibull-measurement error using the autocorrelation and let the two-sided Weibull distributed notional distribution depend on observed characteristics. Unfortunately, this method is not available. It would be an interesting topic for further research. However, if I have to make a choice for a particular method, then I 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 estimates of the IWFP methods and the Maximum Likelihood method can not be directly compared. 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 my estimates comparable with each other, I 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. I calculate the probability of being covered by nominal wage rigidity, conditional on not being covered by real wage rigidity as follows:

$$P^c_{N,t} = \frac{P_{N,t}}{P_{F,t} + P_{N,t}} = \frac{P_{N,t}}{1 - P_{R,t}}. \tag{3.12}$$

3.5 Determinants of wage rigidity

Once estimates for wage rigidity are established, a next step is studying differences in Downward Nominal Wage Rigidity and Downward Real Wage Rigidity 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 variables. It is important to note that the marginal effects of categorical variables are defined as the change from the base level. This analysis does not give any information about causal effects. Probably some variables are 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 gives only 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, estimates for wage rigidity are only available for the entire sample that is used and not per individual. 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 sample of only women. Dickens et al. (2007a) uses the correlation 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). I will illustrate this with an example. Assume you are interested in the effect of having a high income on wage rigidity. By now applying the IWFP procedure on a group with a high income and on a group with a low income, you may erroneously conclude that a high income has a large positive effect on 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.

Therefore I will use a different procedure. The IWFP procedure will be applied to samples where multiple variables are equal, e.g. *male, aged 25-45,* $1 - 2\times$ *modal income*. Since making groups where all available explanatory variables are equal would be technically infeasible in terms of computation time, I use in every regression one variable of interest and a fixed set control variables, and the sample is split accordingly. I am able to use this procedure since my data set is large (26,601,768 observations), therefore splitting the sample into several groups would 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 vulnerable 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. Using my approach the characteristics of those who are scheduled for a wage cut and those who are not, are the same for every particular group. 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 I do not estimate the parameters of the error-correction step for each group, but instead apply the error correction using the parameters previously obtained for the entire sample.

In the Maximum Likelihood model, the degree of wage rigidity depends on the year. A straight forward way to study the determinants of wage rigidity is to allow the degree of wage rigidity to depend on other explanatory variables and estimate the entire model again. However, given my sample size and the number of parameters to estimate (± 130) this is infeasible. Therefore I 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. The probability of being in a certain regime will depend on explanatory variables using a logit specification. I will report the marginal effects, where I will use two specifications. First, I will present results where only the fixed set of controls are included as well as one variable of interest. These results can be compared to the marginal effects of the simple and model-based IWFP methods. Second, I will report the results for a model where all explanatory variables are included. This model does not suffer from an omitted variable bias. In this analysis I will use the IWFP definition for the amount of DNWR (the conditional probability $P^c_{N,t}$) instead of the unconditional probability $P_{N,t}$. This makes the results of the fractional logit models comparable.

Chapter 4

Data

For my research data is obtained from Statistics Netherlands (CBS). More specifically, data from the Social Statistical files (SSB) for 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').

4.1 Types of wages

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 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. For salaried workers, when no wage change takes place, dividing their salary by the actual hours worked could lead to spurious wage changes. When the actual hours worked of hourly workers change and the salary is not divided by hours worked this will also be reported as a spurious wage change. Lunnemann and Wintr (2010) discuss this problem in detail. The researchers decide to use annual wages for salaried workers and hourly wages for hourly workers.

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. I did experiment with hourly wages. These hourly wages clearly showed in some years that a part of the wage changes were shifted[1]. This stems from the fact that the number of working days in a month depends on the day of the week that the month started. Some companies report hours worked based on these working days, while others use some form of norm hours. It is known that hourly workers are very uncommon in the Netherlands (Schravesande, 2012). For these reasons I do not divide wages by the number of hours worked. I focus on the year to year change in monthly salary for the month of October. In October no specific incidental wage changes take place, which could distort my estimates.

The retention tax can be declared per month, half year, year or per four weeks. The dates of the four week declaration period change every year and are, of course, not synchronized with the first of the month. In the dataset of October the salary from the first of October until the last day of the declaration period is given. For example in 2014 the tenth four week

[1]With for example an additional spike at -4 % in the wage change histogram

declaration period will start on the 8th of September 2014 and end on the 5th of October 2014. I will reconstruct the entire tenth four week declaration period by combining information form subsequent monthly data sets.

4.2 Sample selection

The data consists of job-stayers and switchers. To make the estimates comparable with other studies I will confine the analysis to job-stayers. Furthermore I will remove some observations. Since the CPB Bureau for Economic Policy Analysis is interested in how companies adapt at an aggregate level I will only consider 'substantial' jobs: jobs that have a substantial effect on the wage bill of a company. In some previous studies part-timers are removed from the sample[2], but since more than half of all employees is a part-timer I will not remove those observations. The following observations are removed:

- *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 my sample with 2 %. For the model-based IWFP I do not delete this observations to follow Dickens et al. (2007b).
- *Jobs of less than 12 hours a week.* Those observations do not have a significant impact on the company level and the number of hours worked fluctuates. This could cause spurious wage changes. Considering only jobs of more than 12 hours a week is in accordance with the Dutch definition of employment (Centraal Planbureau, 2011, p.63).
- *Interns, temporary workers (uitzendkrachten), director and major shareholders (Directeur groot aandeelhouders), people in the Social Employment Law (WSW) and on-call staff.* Those employees do not negotiate (temporary workers, director and major shareholders, people in the Social Employment Law and on-call staff) or are not considered employees (Interns).
- *Employees below 23 and above 64 years old.* The employees below 23 often work next to their study were 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. This age-based selection is common in CPB labour market studies.

4.3 Explanatory variables

To explain differences in wage rigidity I use the explanatory variables that are shown in Table 4.1. Control variables (depicted in the table by control-variable: Yes) will be included in each performed fractional logit regression, together with one of the variables of interest. I have information on education for one third of the observations and information on profit is available for about one third of the companies.

Age is classified into three groups: 23-34, 35-49, 50-64. For immigrant I will use the definition of 'allochtoon' and consider both second and first generations 'allochtoon' as immigrants. For education three groups are distinguished according to the classification of Statistics Netherlands. For wages I use three groups: '$< 1\times$ modal', '$1 - 2\times$ modal' and '$> 2\times$ modal'. It is important to note the this definition of modal wage does not come 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. Furthermore I include a sector and a year dummy to incorporate sector- and time-specific heterogeneity.

[2]For example: Messina et al. (2010), Du Caju et al. (2007)

Table 4.1: Explanatory variables used in the fractional logit regressions

Explanatory variable	**Groups**			**Control**
Personal				
Age	23-34	35-49	50-64	Yes
Gender	Male	Female		Yes
Country of origin	The Netherlands	Other		No
Education	Low	Middle	High	No
Province/Sector	Normal/Growth	Shrinkage		No
Job				
Wage	$< 1\times$ modal	$1 - 2\times$ modal	$> 2\times$ modal	Yes
Hours	Full-time	Part-time		No
Contract type	Open	Fixed		Yes
Company				
Company size	Small	Medium	Large	Yes
Profit last year	< 0	≥ 0		No
Employment growth last year	< 0	≥ 0		No
Bonus culture	Ratio $< Q_{25}$	$Q_{25} \geq$ Ratio $< Q_{75}$	Ratio $\geq Q_{75}$	No
Heterogeneity				
Sector	According to SBI-classification			Yes
Year				Yes

Chapter 5

Results

5.1 The simple IWFP method

I have estimated DRWR and DNWR using the simple IWFP method. For the inflation expectation the estimated inflation expectation of the Maximum Likelihood method is used. The results are shown in Figure 5.1. Overall a substantial amount of DNWR is found (23 %). The estimates of DRWR are overall lower than those of DNWR, with an average of 10 %. 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 to the absence of DRWR. The results of the simple IWFP method indicate a low amount of real rigidity. These results are in line with my expectations of the Dutch labor market where wage moderation is common.

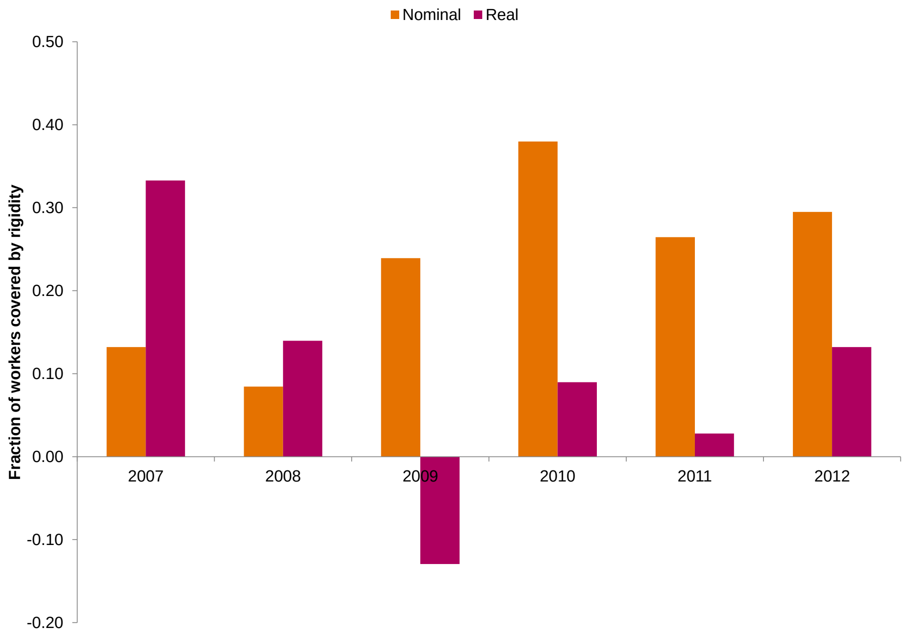
5.2 The model-based IWFP method

In Figure 5.2 the estimates using the model-based IWFP method are shown. In this analysis I have set the amount of symmetric rigidity to zero. Here I deviate from the 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 %. This method estimates that 24 % of the workers is covered by DNWR, conditional on not being covered by DRWR, and 39 % is covered by DRWR. The results without this restriction are presented in Appendix B.

5.3 The Maximum Likelihood method

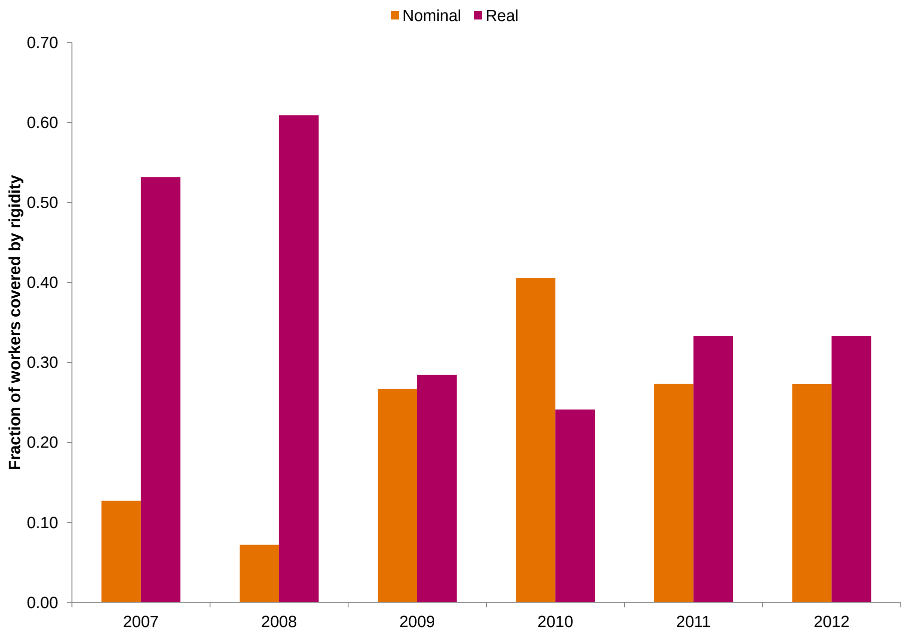
The results of the Maximum Likelihood method are presented in Figure 5.3. The fraction observations in the nominal rigidity regime is estimated at 18 %. According to the Maximum Likelihood method DRWR equals 67 % in the Netherlands. This seems to be implausible. The Maximum Likelihood method results in a standard deviation of the inflation expectation of 1.28 %. This means that about 10 % of all workers expect a negative inflation rate. Furthermore also the fraction of workers covered by DNWR, conditional on not being covered by DRWR is very high.

When diving further into the method, the results seem to emerge from the normality assumption of the notional wage change distribution. This is demonstrated by a simulation exercise, that is presented in Figure 5.4. In this figure the observed distribution is shown in Figure 5.4a. Using the estimated parameters it is possible to simulate wage changes. First the notional wage change is drawn. This is depicted in Figure 5.4b. Then for every observation an inflation expectation is simulated, using the found parameters, which is shown in Figure 5.4c. Now the regime



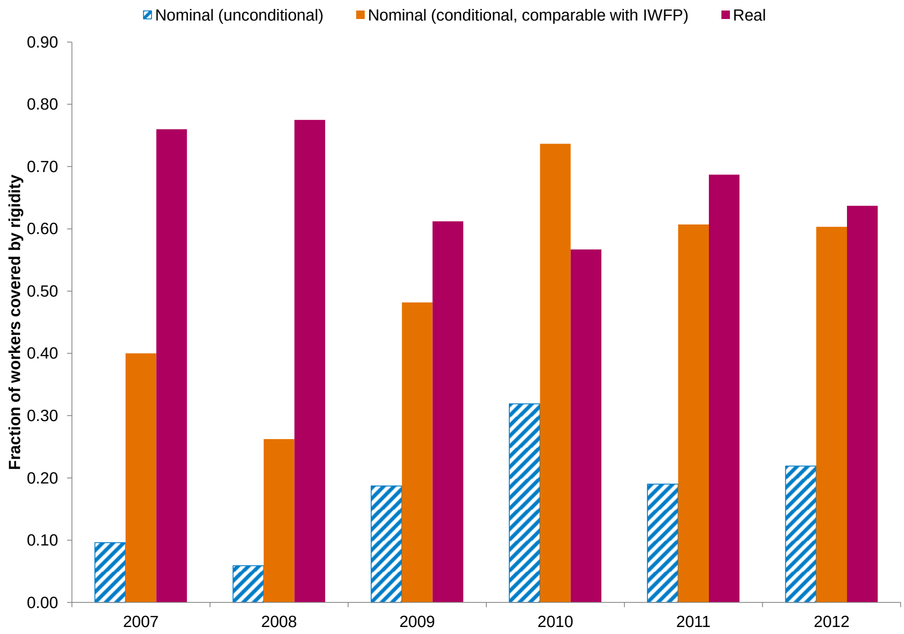
Source: own calculations based on Statistics Netherlands microdata

Figure 5.1: The estimated degree of wage rigidity using the simple IWFP method



Source: own calculations based on Statistics Netherlands microdata

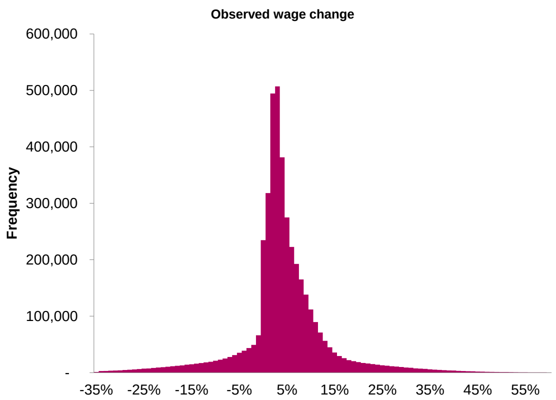
Figure 5.2: The estimated degree of wage rigidity using the model-based IWFP method



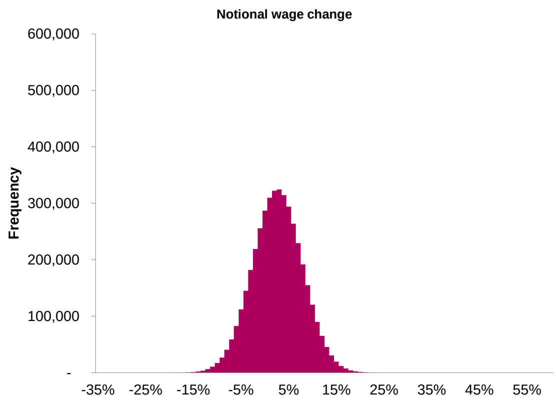
Source: own calculations based on Statistics Netherlands microdata

Figure 5.3: The estimated degree of wage rigidity using the Maximum Likelihood method

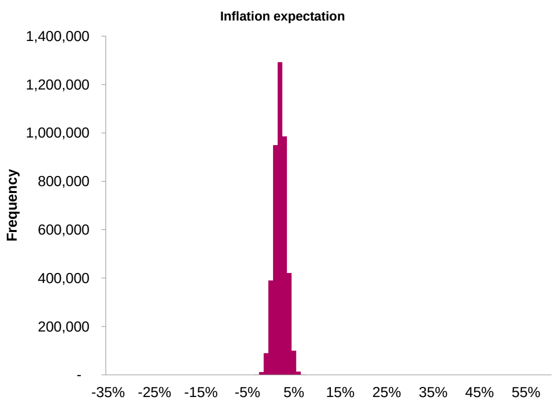
is drawn using the estimated regime probabilities and wages are set accordingly. After adding measurement error, the result is the distribution from Figure 5.4d. The simulated distribution looks almost identical to the observed distribution. This is a sign that this model is able to replicate most of the properties of the observed wage change distribution. However, it is observed 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 and notional wage changes are two-sided Weibull distributed, 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. If that is the 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. Using a normal distribution will probably lead to an underestimate of the likelihood of observations falling in the free regime, leading to a lower probability of coming from the free regime and therefore to an overestimate of the probability of belonging to the real rigidity regime. If the fraction of workers falling in the free regime is underestimated this also influences the results of the probability of being covered by DNWR, conditional on not being covered by DRWR, since $P_{N,t}$ is divided by $P_{N,t} + P_{F,t}$. An underestimate of $P_{F,t}$ will therefore lead to an overestimate of $P^c_{N,t}$. Therefore, the high amounts of DRWR and DNWR that I measure using the ML-method do not come as a surprise, since, as discussed in Section 3.4 the normality assumptions might not hold and my period of observation is characterized as a low inflation period with an inflation rate close to the median, especially for the years 2009-2012.



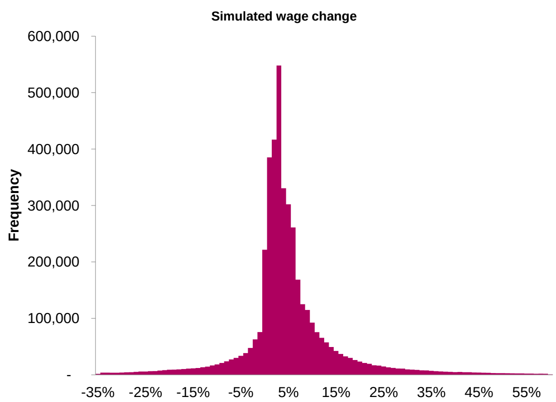
(a) Observed wage change distribution



(b) Simulated notional wage change distribution



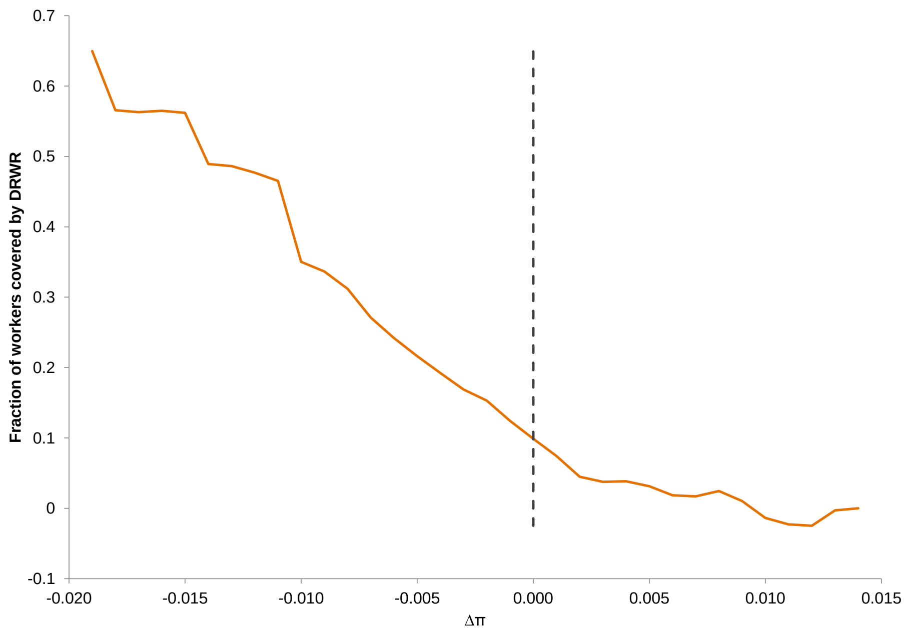
(c) Simulated inflation expectation distribution



(d) Simulated wage change distribution

Source: own calculations based on Statistics Netherlands microdata

Figure 5.4: Histograms of the simulated, observed and notional distribution for 2007, obtained using the Maximum Likelihood method



Source: own calculations based on Statistics Netherlands microdata

Figure 5.5: Effect of changing the rigidity threshold on the estimate of DRWR using the IWFP simple method

5.4 Sensitivity analysis

I perform an additional sensitivity analysis on the expected inflation rate parameter π_t in the simple IWFP method. This inflation rate parameter was set equal to the estimated inflation rate according to the Maximum Likelihood method ($\bar{\pi}_{t,ML}$). I vary the parameter π_t between $\bar{\pi}_{t,ML} - 0.019$ and $\bar{\pi}_{t,ML} + 0.014$ in steps of 0.001 and report the obtained real wage rigidity. If the inflation rate exceeds the median for a certain year, the reported average DRWR will not contain that year, since no information on that year is available.

From the results, as shown in Figure 5.5, it becomes clear that the expected inflation rate has a large influence on the estimated amount of DRWR. If a lower expected inflation rate was chosen the estimated amount of real wage rigidity would have been much higher. The amount of DNWR is not affected by π_t. The model-based IWFP method estimates the parameter π_t endogenous, and therefore does not suffer from this problem.

5.5 Method comparison

When inspecting the results, it becomes clear that all three methods give very different results. Estimates wage rigidity differ largely. While the simple IWFP method detects 10 % of real wage rigidity, 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, differences are smaller. The divergence of the results might be explained by the fact that all three methods use different distributional assumptions: 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.

Since it is observed the results of all three methods differ substantially, it appears that a complex model is required to estimate real wage rigidity. The model-based IWFP method takes into account all features of the wage change distribution (including for example the autocorrelation). This method estimates the fraction of DRWR at 39 % and DNWR at 24 %.

Furthermore the estimates of DNWR and DRWR differ over the years. The simple IWFP even presents negative estimates of the fraction of wages covered by real rigidity. Another interesting observation is the fact that nominal wage rigidity is lower in 2007 and 2008 compared to 2009-2012, while the model-based and ML estimates show an increase in DRWR. In those years the estimated inflation expectation of both the model-based and Maximum Likelihood method was considerably higher than the years thereafter. In theory the estimates should not depend on the inflation expectation, which would imply that the amount of DNWR has increased after 2008. 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.

5.6 Determinants of wage rigidity

Now wage rigidity is estimated, I continue with studying the determinants of wage rigidity. For the simple and model-based IWFP method I perform the IWFP procedures on groups of the sample in order to estimate the amount of DNWR and DRWR for each group. I use in every regression the variable of interest and a fixed set of control variables. A fractional logit model is estimated to explain these wage rigidity outcomes, using worker and firm characteristics as explanatory variables. The observations are weighted by the number of observations in the group.

According to the simple IWFP procedure (Table 5.1) company size has a large negative impact on DNWR, while having a positive impact on DRWR. This is not surprising: large companies have the ability to replace someone, if he or she is not willing to accept a nominal wage cut, while small companies might be dependent on specific skills of one employee. A higher degree of DRWR might be due to the fact that large companies have negotiations with unions to agree upon a collective bargaining agreement. Often unions demand inflation compensation, which is a form of DRWR at the aggregate, rather than individual level. Age has a small effect on DNWR, while having a large negative influence on DRWR. Differences over gender are small. Not surprisingly a high wage has a positive relation 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. This might indicate that workers are to some extend willing to accept real wage cuts in favor of employment. The effect of fixed-end contracts seems to be small. As discussed in Section 3.5 these results do not have a causal interpretation.

The most notable observation when inspecting the results for the model-based IWFP method (Table 5.2) is that the estimated marginal effects show a lot of symmetry with the results of the simple IWFP method. Also using this method it is estimated that larger companies show less DNWR, but more DRWR and that higher wages are associated with more real rigidity. However, for some variables the results of both methods differ substantially (e.g. age, bonus culture, profit last year and education). The differences in marginal effects 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[1]. However given

[1] I thank B. Wouterse and S.B. Gerritsen for this suggestion

my 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 I have not weighted with the obtained standard errors. This is common practice in the existing literature (Messina et al., 2010; Dickens et al., 2007a,b).

For the Maximum Likelihood method I present two types of results. In the first column of Table 5.3 results are presented where in every regression the variable of interest and certain control variables are used. This makes these results comparable to those presented in Table 5.1 and 5.2. In the second column marginal effects are presented for the model specification where all explanatory variables are included. The presented standard errors allow clustering per individual.

The results of the first Maximum Likelihood specification show some 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 be larger, in general. Both methods find a positive effect of age on being covered by DNWR and DRWR. Next to the other IWFP methods, the ML method also finds a negative effect of company size on DNWR, while having a small positive effect on DRWR. Part-timers have less rigidity in general according to the marginal effects of Goette et al., while the model-based IWFP method only finds a negative effect on DNWR and not on DRWR. All methods find that people with a high education have an increased probability of being covered by DNWR and DRWR. This might be explained that the highly educated are better negotiators or have a better negotiation position, since they posses specific skills.

Especially for the smaller effects, however, there are notable differences between the model-based method and the Maximum Likelihood 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 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 experienced zero or positive employment growth in the previous year. 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 in the previous year. Stricter employment protection for long-tenured (and so often older) workers and workers on open-end contracts may be one of the explanations.

Unfortunately, my data does not contain any information on the degree of organization. Descriptive statistics on the degree of organization, based on the (much smaller) Dutch Labour Force Survey Sociaal-economische Raad (2013) shows that the degree of organization 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 organized groups and the characteristics that are positively related to wage rigidity, suggests that being highly organized 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 organized 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).

Overall the results of all three methods show a lot of similarities. This is an indication that all three methods measure the same quantity. 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 comparing estimates of countries using the same method is possible in principle with every method. However, for the Maximum Likelihood method only estimates in a similar inflation environment (low or high) can be compared, since I did find indications that the amount of real and nominal rigidity is overestimated in a low inflation environment. Furthermore, if one wants to get an idea about the number of people who have a rigid wage, the choice of the method has a large influence.

Table 5.1: Marginal Effects for the simple IWFP method (robust standard errors in parenthesis)

		DNWR		**DRWR**	
		dy/dx		dy/dx	
Controls					
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	$< 1\times$ modal				
	$1 - 2\times$ modal	-0.016	(0.000050)	0.078	(0.000148)
	$> 2\times$ 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)
Other explanatory variables					
Hours	Full-time				
	Part-time	-0.072	(0.000058)	-0.141	(0.000155)
Profit last year	< 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 last year	≥ 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 $\geq Q_{75}$	-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.
Source: own calculations based on Statistics Netherlands microdata

5.7 International perspective

It is possible to compare my estimates to other countries. Therefore I have collected estimates of other countries from several papers. The results are presented in Figure 5.6 and Figure 5.7.

Table 5.2: Marginal Effects for the model-based IWFP method (robust standard errors in parenthesis)

		DNWR dy/dx		**DRWR** dy/dx	
Controls					
Age	25-35				
	36-50	0.066	(0.000051)	0.015	(0.000122)
	51-65	0.082	(0.000065)	0.071	(0.000150)
Gender	Male				
	Female	0.016	(0.000066)	0.033	(0.000134)
Wage	$< 1\times$ modal				
	$1 - 2\times$ modal	-0.033	(0.000056)	0.021	(0.000130)
	$> 2\times$ modal	0.053	(0.000102)	0.114	(0.000205)
Contract type	Open-end				
	Fixed-end	-0.013	(0.000072)	-0.016	(0.000166)
Company size	Small				
	Medium	-0.215	(0.000057)	0.062	(0.000128)
	Large	-0.299	(0.000054)	0.020	(0.000118)
Other explanatory variables					
Hours	Full-time				
	Part-time	-0.107	(0.000063)	-0.003	(0.000135)
Profit last year	< 0				
	≥ 0	-0.011	(0.000077)	-0.013	(0.000179)
Province/Sector	Normal/Growth				
	Shrinkage	0.010	(0.000070)	-0.060	(0.000143)
Employment growth last year	≥ 0				
	< 0	-0.015	(0.000080)	-0.005	(0.000171)
Bonus culture	Ratio $< Q_{25}$				
	$Q_{25} \geq$ Ratio $< Q_{75}$	-0.008	(0.000180)	0.033	(0.000235)
	Ratio $\geq Q_{75}$	0.005	(0.000137)	0.013	(0.000198)
Country of origin	The Netherlands				
	Other	-0.013	(0.000062)	-0.013	(0.000124)
Education	Low				
	Middle	0.026	(0.000113)	0.017	(0.000224)
	High	0.044	(0.000139)	0.049	(0.000265)

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.
Source: own calculations based on Statistics Netherlands microdata

Table 5.3: Marginal Effects for the Maximum Likelihood method (clustered standard errors in parenthesis)

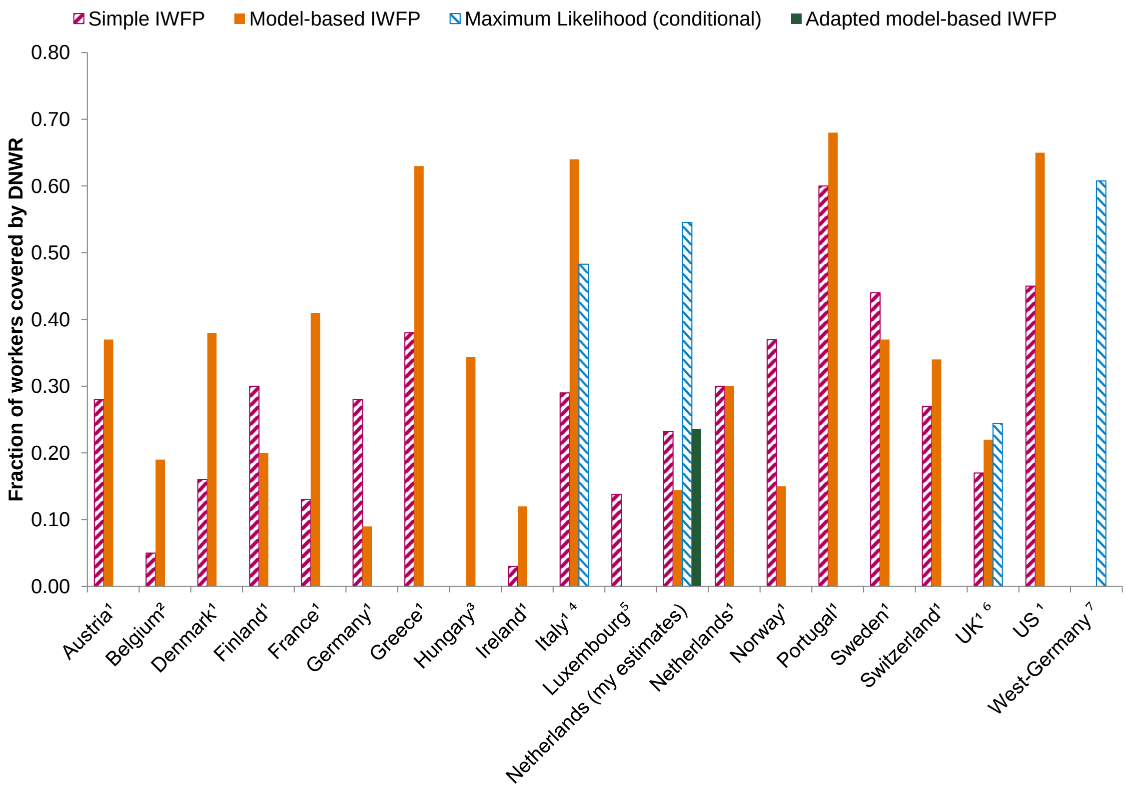
		Controls + 1 Explantory variable				All variables			
		DNWR (conditional)		**DRWR**		**DNWR (conditional)**		**DRWR**	
		dy/dx		dy/dx		dy/dx		dy/dx	
Controls									
Age	25-35								
	36-50	0.102	(0.000027)	0.136	(0.000130)	0.066	(0.000142)	0.131	(0.000269)
	51-65	0.139	(0.000031)	0.185	(0.000142)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

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.
Source: own calculations based on Statistics Netherlands microdata

It is important to note that the time period of different estimates is not (always) equal.

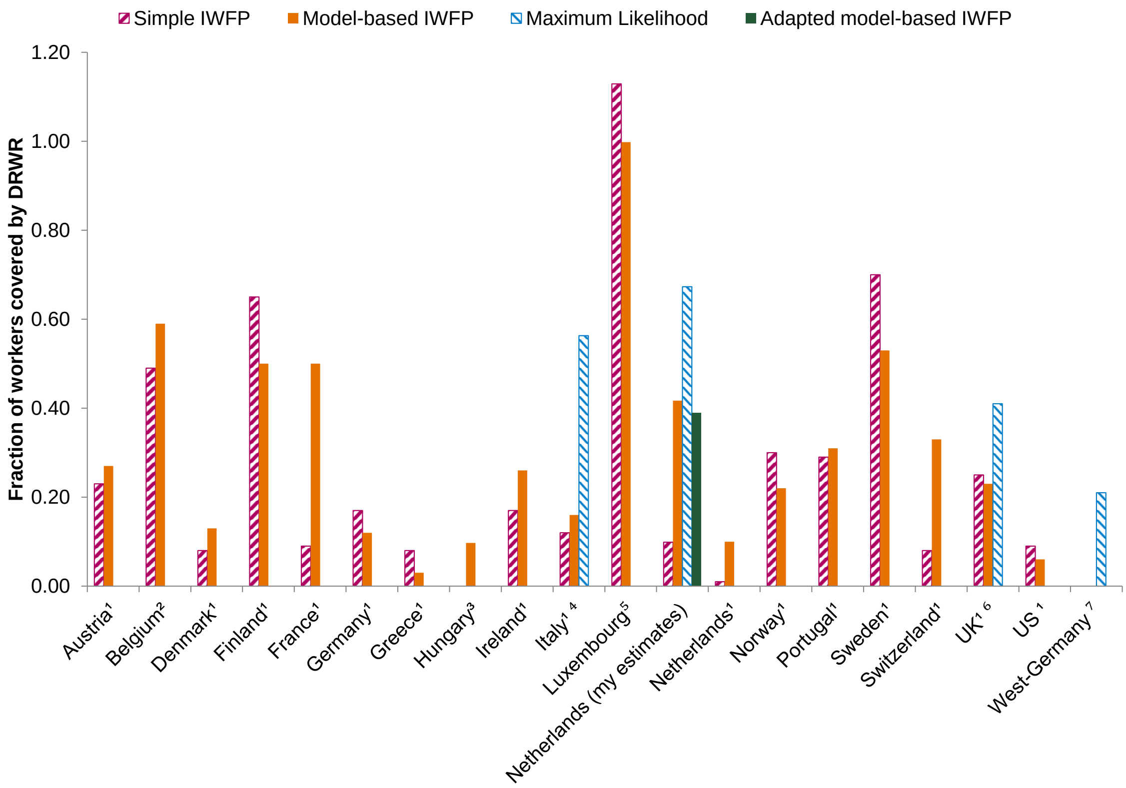
The first thing to notice is that estimates of the three discussed methods differ quite a lot from each other. This is in line with my findings that the estimates of wage rigidity differ substantially, depending on the method used. A part of the variability might be explained by the fact that the time period and data set of the various method differ. The differences, especially with respect to DNWR, between the IWFP methods and the Maximum Likelihood method appear to be smaller for other countries than for my data; the Maximum Likelihood estimate of DNWR lies in between those of the model-based en simple IWFP method for the UK and Italy. This might be explained by the fact that in my data set 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 DNWR and DRWR.

Furthermore it can be seen that the Netherlands has an average amount of DNWR compared to other countries (according to all methods). However for DRWR no clear picture emerges. The estimates according to the simple IWFP method indicate a relatively low amount of real wage rigidity, while the Maximum Likelihood method gives the highest estimates for real wage rigidity compared to the other countries with Maximum Likelihood estimates. DRWR is about average according to the model-based IWFP method.



[1] Dickens et al. (2007a) and Dickens et al. (2007b) (Figure 3 and Figure 4, respectively)
[2] Du Caju et al. (2007) (Table 3 and Table 6)
[3] Kátay (2011) (Non-technical summary)
[4] Devicienti et al. (2007) (Table 3 - Average (benchmark estimates))
[5] Lunnemann and Wintr (2010) (Table 2)
[6] Barwell and Schweitzer (2007) (Table 1)
[7] Bauer et al. (2007) (Average of Table 1)
Note: I have converted unconditional probabilities of ML studies to conditional probabilities in order to make the estimates comparable.
Source: own calculations based on Statistics Netherlands microdata

Figure 5.6: The estimated degree of Downward Nominal Wage Rigidity (DNWR) in various countries



[1] Dickens et al. (2007a) and Dickens et al. (2007b) (Figure 3 and Figure 4, respectively)
[2] Du Caju et al. (2007) (Table 3 and Table 6)
[3] Kátay (2011) (Non-technical summary)
[4] Devicienti et al. (2007) (Table 3 - Average (benchmark estimates))
[5] Lunnemann and Wintr (2010) (Table 2)
[6] Barwell and Schweitzer (2007) (Table 1)
[7] Bauer et al. (2007) (Average of Table 1)
Source: own calculations based on Statistics Netherlands microdata

Figure 5.7: The estimated degree of Downward Real Wage Rigidity (DRWR) in various countries

Chapter 6

Conclusion

In this thesis I have studied the amount of wage rigidity among job-stayers in the Netherlands. The amount of Downward Nominal Wage Rigidity (DNWR) appears to be about average compared to other countries (24 %) according to the model-based IWFP method. Also the fraction of observations covered by Downward Real Wage Rigidity (DRWR) is average (39 %) according to this method. This is not in line with my hypothesis that the amount of DRWR would be relatively low and the amount of DNWR relatively high. I have also researched the determinants of wage rigidity. I find that large companies have less nominal wage rigidity than small and middle-sized companies, while showing more real wage rigidity. Furthermore, my analysis of the determinants of Dutch wage rigidity shows that the presence of wage rigidity is unevenly distributed among groups of workers. I find 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 experienced zero or positive employment growth in the previous year. Also people with a higher wage have a higher degree of real wage rigidity. I have indications that people working in a shrinking sector province combination are to some extend willing to accept real wage cuts in favor of employment. I also find that the amount of real wage rigidity decreases and nominal rigidity increases in a low inflation environment.

Furthermore I conclude that the three commonly used methods for estimating wage rigidity differ substantially. Not only with respect to the methodology, but also with respect to the amount of rigidity they estimate. The main problem with most sophisticated methods is that 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. If the two-sided Weibull assumption for the notional distribution is correct, this might lead to an overestimate of the fraction of wages set under the DRWR regime according to the Maximum Likelihood method. The model-based IWFP method is preferred since it takes into account most features of the wage change distribution, while using mild assumptions. 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 is an indication that all three methods measure the same quantity, which implies that comparing estimates of countries using the same method is possible in principle with every method. However, for the Maximum Likelihood method only estimates in a similar inflation environment (low or high) can be compared, since I did find indications that the amount of real and nominal rigidity is overestimated in a low inflation environment. Furthermore, if one wants to get an idea about the number of people who have a rigid wage, the choice of the method has a large influence.

This thesis shows that identifying wage rigidity can lead to different results when the underlying notional distribution is unknown. Different assumptions on the unobserved notional distribution lead to completely different outcomes. Therefore I think further research should focus on the notional wage change distribution. Identifying the notional distribution in a deflation environment might give clues about the form of the notional distribution, however a wage change distribution in a deflation environment might not be comparable to that in an inflation environment. A real life social experiment of how wages are determined during negotiations could also generate interesting insights regarding the notional distribution. Especially as different levels of inflation are taken into account.

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 my 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.

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Nomenclature

a	Shape parameter of the two-sided Weibull-distribution
b_t	Scale parameter of the two-sided Weibull-distribution in year t
$B_t(\alpha)$	Integral of two two-sided Weibull distributions (with certain boundaries)
$C_t(\alpha, \beta)$	Integral of three two-sided Weibull distributions (with certain boundaries)
$c_{n,t}$	The fraction of nominal wage cuts in year t
$c_{r,t}$	The fraction of real wage cuts in year t
$D_1(\alpha, \beta \| a, b_1, b_2)$	Integral of two two-sided Weibull distributions (with certain boundaries)
$D_2(\alpha, \beta \| a, b_1, b_2)$	Integral of two two-sided Weibull distributions (with certain boundaries)
$d_{i,t}$	True (logarithmic) wage change of individual i in year t
$d^o_{i,t}$	Observed (logarithmic) wage change of individual i in year t
$d^n_{i,t}$	Notional wage change
$d^r_{i,t}$	Real adjusted wage change
$F_t(x)$	Cumulative wage change distribution for the two-sided Weibull
$f_{n,t}$	The fraction of nominal wage freezes in year t
$f_{r,t}$	The fraction of real wage freezes in year t
$\mathbf{g}_{i,t}$	Vector containing a 1 at position j where $u_j > d^o_{i,t} > l_j$
$\mathbf{h}_{i,t}$	Vector of indicators $h_{i,t,j}$
$h_{i,t,j}$	Indicator if observation i is a switcher from year t to $t+1$
K	The number of cells in the histogram
l_j	Lower bound of cell j
$L_{t,j}$	Lower bound for defining switchers
$\mathbf{m}_t$	Vector containing the fraction of observations in each of the $K-1$ cells
$\mathbf{m}^*_t$	Vector containing the fraction of observations in each of the K cells
M_t	The median of the wage change distribution in year t
$m^c_{j,t}$	Element j of $\mathbf{m}_t$

$\mathbf{m}_t^o$ Observed vector containing the fraction of observations in each of the $K-1$ cells

N_t The number of observations containing information for year t

$N_{t,t+1}$ The number of observations containing information for year t and $t+1$

$\hat{\mathbf{\Omega}}_c$ Estimated variance-covariance matrix for the parameters for the correction step

$p_{F,t}$ Probability of belonging to the flexible regime in year t

p_m Probability of making a measurement error

$p_{m|e}$ Probability of making an error conditional on being prone to make errors

$p_{N,t}^c$ Probability of being covered by downward nominal wage rigidity in year t, conditional on not being covered by DRWR

p_{ne} Probability of not being prone to measurement errors

$p_{N,t}$ Probability of being covered by downward nominal wage rigidity in year t

$p_{R,t}$ Probability of being covered by downward real wage rigidity in year t

$\mathbf{q}$ Vector with values of the discrete wage change distribution

$\mathbf{R}_t$ Transformation matrix for transforming $\mathbf{m}_t$ to $\mathbf{m}_t^o$

$\mathbf{R}_{t,,K}$ Vector with elements defined in Equation A.4

$\mathbf{S}_t$ Matrix with the expected number of switchers between cells

u_j Upper bound of cell j

$U_{t,j}$ Upper bound for defining switchers

$W_t(\alpha)$ Integral of the two-sided Weibull distribution (with certain boundaries)

$w_t(x|a,b)$ Two-sided Weibull density

$w_{i,t}$ True log wage of individual i in year t

$w_{i,t}^o$ Observed log wage of individual i in year t

$\mathbf{x}_{i,t}$ Explanatory variables of individual i at time t

$z_{j,t}$ Fraction of notional real adjusted wages that would fall in cell j of the histogram

$\epsilon_{i,t}$ Uniform distributed variable over the unit interval

$\eta_{i,t}$ Measurement error of individual i in year t if an error is made

$\eta_{i,t}'$ Measurement error of individual i in year t

$\Gamma(x)$ Gamma function

$\hat{\sigma}_{d_t d_{t+1}}$ Empirical first order auto-covariance

λ_t The fraction of observations below the inflation expectation π_t

β Parameter vector

$\mu_{i,t}$ Uniform distributed variable over $[-p_{m|e}, 1-p_{m|e}]$

$\omega_{i,t}$	Unexplained part of a wage change
$\Phi_t(x)$	Cumulative normal distribution with mean π_t and variance $\sigma^2_{\pi,t}$
$\pi_{i,t}$	Inflation expectation of individual i in year t
π_t	Mean inflation expectation in year t
σ^2_m	Variance of the measurement error
$\sigma^2_{\omega,t}$	Variance of $\omega_{i,t}$
$\sigma^2_{\pi,t}$	Variance of $\pi_{i,t}$
$\tau_{i,t}$	Uniform distributed variable over $[p_{ne} - 1, p_{ne}]$
υ_t	The fraction of observations above $M_t + (M_t - \pi_t)$

Appendix A

Technical details of the correction step of the model-based IWFP method

The IWFP methodology assumes that a fraction of the employees is prone to reporting/measurement errors. I will denote the fraction not prone to measurement errors as p_{ne}. Furthermore it is assumed that someone who is prone to errors, has a measurement error with probability $p_{m|e}$. Now the model assumed by the IWFP is

$$w_{i,t} = w_{i,t-1} + d_{i,t} \tag{A.1}$$

$$w^o_{i,t} = w_{i,t} + \eta'_{i,t} \text{ where } \eta'_{i,t} = \begin{cases} 0 & \text{if } \mu_{i,t} > 0 \text{ or if } \tau_i > 0 \\ \eta_{i,t} & \text{otherwise} \end{cases}, \tag{A.2}$$

where $w_{i,t}$ is the true logarithm of the wage, $w^o_{i,t}$ is the logarithm of the observed wage, $d_{i,t}$ is the true (logarithmic) wage change, $\eta_{i,t}$ is the measurement error of a wage observation, $\eta'_{i,t}$ is the measurement error when an error is made. Furthermore $\mu_{i,t}$ and $\tau_{i,t}$ are uniform distributed over $[p_{m|e}, 1-p_{m|e}]$ and $[p_{ne}-1, p_{ne}]$ respectively. The (logarithmic) wage change $d^o_{i,t} = w^o_{i,t} - w^o_{i,t-1}$ is observed. It is assumed that $\eta_{i,t}$ is drawn from a two-sided Weibull with mean zero, shape parameter a and scale parameter b_t. a is constant over time, while b_t is time dependent.

Now the IWFP procedure assumes that wage changes are drawn from a discrete distribution, represented by the vector $\mathbf{q}$, of K known values to approximate the wage change distribution. In the official IWFP procedure 76 values are used. Discrete values are defined between -0.245 and 0.495 in steps of 0.01 or it can take the value zero. Also the upper limits u_j and lower limits l_j for the cells in the histogram are defined (0.005 per cell from both sides). The lower and upper limit of the 'zero' cell are set at -0.00017 and 0.00017, respectively. This means that very small wage changes will be considered as a 'zero' wage change. This is in line with the IWFP methodology (Dickens et al., 2007a, footnote p.199). The fraction of observation in a specific cell is given by the vector $\mathbf{m}^*_t$. However, since the fractions in the histogram should add up till 1, only $K-1$ fractions are estimated, which I will denote with $\mathbf{m}_t$.

Now a vector $\mathbf{g}_{i,t}$ can be defined with a 1 at position j where $u_j > d^o_{i,t} > l_j$. Now, since measurement error will cause autocorrelation, 'switchers' can be identified by setting the variable $h_{i,t,j}$ equal to 1 if $d^o_{i,t} > U_{t,j}$ and $d^o_{i,t+1} < L_{t,j}$ or where $d^o_{i,t} < U_{t,j}$ and $d^o_{i,t+1} > L_{t,j}$, where $L_{t,j}$ and $U_{t,j}$ are defined as upper and lower limits for which an observation is defined as a switcher. The vector of all j $h_{i,t,j}$'s is denoted by $\mathbf{h}_{i,t}$. Now moment conditions can be derived. The first condition is on the fractions of observations in the histogram $\mathbf{m}^o_t = \sum_{i=1}^{N_t} \frac{\mathbf{g}_{i,t}}{N_t}$. Here N_t is the number of observations containing information for year t and $N_{t,t+1}$ is the number of observations containing information for t and $t+1$. The fraction of observations in the histogram should equal a transformation of the true wage changes distributions by errors. The first set of moment condition is defined as

$$\sum_{i=1}^{N_t} \frac{\mathbf{g}_{i,t}}{N_t} = E[\mathbf{m}_t^o] = \mathbf{R}_t \mathbf{m}_t + \mathbf{R}_t (I - 1'_{K-1} \mathbf{m}_t). \tag{A.3}$$

The matrix $\mathbf{R_t}$ is defined by elements x, y as

$$\begin{aligned} R_{t,x,y} = & (1-p_{ne}) p_{m|e}^2 (B_t(u_x - q_y) - B_t(l_x - q_y)) \\ & + (1-p_{ne}) p_{m|e} (1 - p_{m|e}) \left((W_t(u_x - q_y) - W_t(l_x - 1_y)) + (W_{t-1}(u_x - q_y) - W_{t-1}(l_x - q_y)) \right) \\ & + \left(1 - (1-p_{ne})(2p_{m|e} - p_{m|e}^2) \right) I(u_x \geq q_y > l_x), \end{aligned} \tag{A.4}$$

where $W_t(\alpha)$ denotes the integral of the two-sided Weibull distribution and $B_t(\alpha)$ is the integral of two two-sided Weibull distributions with lower and upper limits defined according to

$$B_t(\alpha) = \int_{-\infty}^{\infty} \int_{-\infty}^{\alpha-\beta} w(\gamma|a, b_t) w(\beta|a, b_t) \mathrm{d}\gamma \mathrm{d}\beta \tag{A.5}$$

$$W_t(\alpha) = \int_{-\infty}^{\alpha} w(\beta|a, b_t) \mathrm{d}\beta, \tag{A.6}$$

where $w(x|a, b)$ is defined as the two-sided Weibull density. $\mathbf{R}_{t,,K}$ is a vector with elements defined in Equation A.4. This component is to account for observations belonging to cell $y = K$, since this element is dropped earlier.

The first line of Equation A.4 can be interpreted as the probability of making two errors, being reported in cell x, conditional on being in cell y. The second line can interpreted as the probability of making a single error, being reported in cell x, conditional on being in cell y. Third line is the probability of not making errors, being reported in cell x, conditional on being in cell y. Of course the latter probability is zero if $x \neq y$.

Now a second set of moment conditions is based on the covariance. Here it is assumed that wage changes in year t are uncorrelated with wage changes in year $t+1$. This moment condition can be derived as follows

$$\begin{aligned} & \sum_{i=1}^{N_{t,t+1}} \frac{\left(d_{i,t}^o - \bar{d}_t \right) \left(d_{i,t+1}^o - \bar{d}_{t+1} \right)}{N_{t,t+1} - 1} = E\left[\left(d_{i,t}^o - \bar{d}_t \right) \left(d_{i,t+1}^o - \bar{d}_{t+1} \right) \right] \\ & = E\left[\left(e_{i,t} - E[e_{i,t}] + \eta'_{i,t} - \eta'_{i,t-1} \right) \left(e_{i,t+1} - E[e_{i,t+1}] + \eta'_{i,t+1} - \eta'_{i,t} \right) \right] = -E[\eta'^2_{i,t}] \\ & = -p_{ne} \cdot 0 - (1-p_{ne}) p_{m|e} E\left[\eta^2 \right] = -(1-p_{ne}) p_{m|e} b_t^2 \Gamma \left(1 + \frac{2}{a} \right), \end{aligned} \tag{A.7}$$

where $b_t^2 \Gamma \left(1 + \frac{2}{a}\right)$ is the variance of the two-sided Weibull distribution.

Now the last set of moment conditions is based on the fraction of switchers. This moment condition is based on the fact that the autocorrelation measure depends on three observations which could all have measurement errors. The moment conditions are defined according to

$$\frac{\sum_{i=1}^{N_{t,t+1}} \mathbf{h}_{i,t}}{N_{t,t+1}} = E\left[\frac{\sum_{i=1}^{N_{t,t+1}} \mathbf{h}_{i,t}}{N_{t,t+1}} \right] \mathbf{m}_t^{*}{}' \mathbf{S}_t \mathbf{m}_{t+1}^{*}, \tag{A.8}$$

with

$$
\begin{aligned}
S_{t,x,y} = {} & (1-p_{ne})p_{m|e}^3 \left(C_t(L_t - q_x, q_y - U_{t+1}) + C_t(q_x - U_t, L_{t+1} - q_y)\right) \\
& + (1-p_{ne})p_{m|e}^2(1-p_{m|e}) \left(D_2(L_t - q_x, q_y - U_{t+1}|a, b_t, b_{t-1}) + D_1(L_{t+1} - q_x, q_y - U_t)|a, b_t, b_{t-1})\right) \\
& + (1-p_{ne})(1-p_{m|e})p_{m|e}^2 \left(D_2(L_{t+1} - q_x, q_y - U_t|a, b_t, b_{t+1}) + D_1(L_t - q_x, q_y - U_{t+1})|a, b_t, b_{t+1})\right) \\
& + (1-p_{ne})(1-p_{m|e})p_{m|e}(1-p_{m|e}) \left(W_t(\min(L_t - q_x, q_y - U_{t+1})) + W_t(\min(L_{t+1} - q_x, q_y - u_{t+1}))\right) \\
& + (1-p_{ne})p_{m|e}(1-p_{m|e})p_{m|e} \left(W_{t-1}(L_t - q_x)W_{t+1}(q_y - U_{t+1}) + W_{t+1}(L_{t+1} - q_x)W_{t-1}(q_x - U_t)\right) \\
& + (1-p_{ne})(1-p_{m|e})^2 p_{m|e} \left(I(L_t > q_x)W_{t+1}(q_y - U_{t+1}) + W_{t+1}(L_{t+1} - q_x)I(U_t < q_x)\right) \\
& + (1-p_{ne})p_{m|e}(1-p_{m|e})^2 \left(W_{t-1}(L_t > q_x)I(U_{t+1} < q_y) + I(L_{t+1} > q_y)W_{t-1}(q_x - U_t)\right) \\
& + \left(p_{ne} + (1-p_{ne})(1-p_{m|e}^3)\right) \left(I(L_t > q_x)I(U_{t+1} < q_y) + I(L_{t+1} > q_y)I(U_t < q_x)\right),
\end{aligned} \tag{A.9}
$$

where $C_t(\alpha, \beta), D_1(\alpha, \beta|a, b_1, b_2)$ and $D_2(\alpha, \beta|a, b_1, b_2)$ are defined as:

$$
C_t(\alpha, \beta) = \int_{-\infty}^{\infty} \int_{\eta_{t-1}-\alpha}^{\infty} \int_{\eta_t-\beta}^{\infty} w(\eta_{t-1}|a, b_t)w(\eta_t|a, b_t)w(\eta_{t+1}|a, b_t)\mathrm{d}\eta_{t+1}\mathrm{d}\eta_t\mathrm{d}\eta_{t-1} \tag{A.10}
$$

$$
D_1(\alpha, \beta|a, b_1, b_2) = \int_{-\infty}^{\alpha} \int_{-\infty}^{\eta_1+\beta} w(\eta_2|a, b_2)w(\eta_1|a, b_1)\mathrm{d}\eta_2\mathrm{d}\eta_1 \tag{A.11}
$$

$$
D_2(\alpha, \beta|a, b_1, b_2) = \int_{-\infty}^{\beta} \int_{\eta_1-\alpha}^{\infty} w(\eta_2|a, b_2)w(\eta_1|a, b_1)\mathrm{d}\eta_2\mathrm{d}\eta_1. \tag{A.12}
$$

The terms in Equation A.9 can be interpreted as follows: The first term represents cases where all three consecutive observations are distorted by measurement error. The second term is for cases where the first two observations contain measurement error, while the last do not, the third term for no error in the first observations while two errors in the second, the fourth term is for only measurement error in the middle observation, the fifth term is for an error in the first and last observation, the sixth term for an error in the last observation, the seventh is for an error in the first observation. The last term represents cases where no errors are made (either due to the fact that some individual is not prone to errors or simply because the individual did not make them.

Now, by using Equation A.3 $\mathbf{m}_t$ can be rewritten to

$$
\mathbf{m}_t = \left(\mathbf{R}_t^{-1} - \mathbf{R}_{t,,K}\mathbf{1}'_{K-1}\right)^{-1}\left(\mathbf{m}_t^o - \mathbf{R}_{t,,K}\right). \tag{A.13}
$$

Now since $\mathbf{m}_t^o$ is observed and known, and $\mathbf{R}_t$ and $\mathbf{R}_{t,,K}$ are functions of the parameters $a, b_t, p_{ne}, p_{m|e}$ the problem is largely reduced and only 3 parameters need to be estimated. It is even possible to replace b_t with a function of the parameters a, p_{ne} and $p_{m|e}$ by using the empirical first order auto-covariance $\hat{\sigma}_{d_t d_{t+1}}$.

$$
b_t = \sqrt{\left(\frac{-\hat{\sigma}_{d_t d_{t+1}}}{p_{m|e}(1-p_{ne})}\right) \Big/ \Gamma\left(1 + \frac{2}{a}\right)}. \tag{A.14}
$$

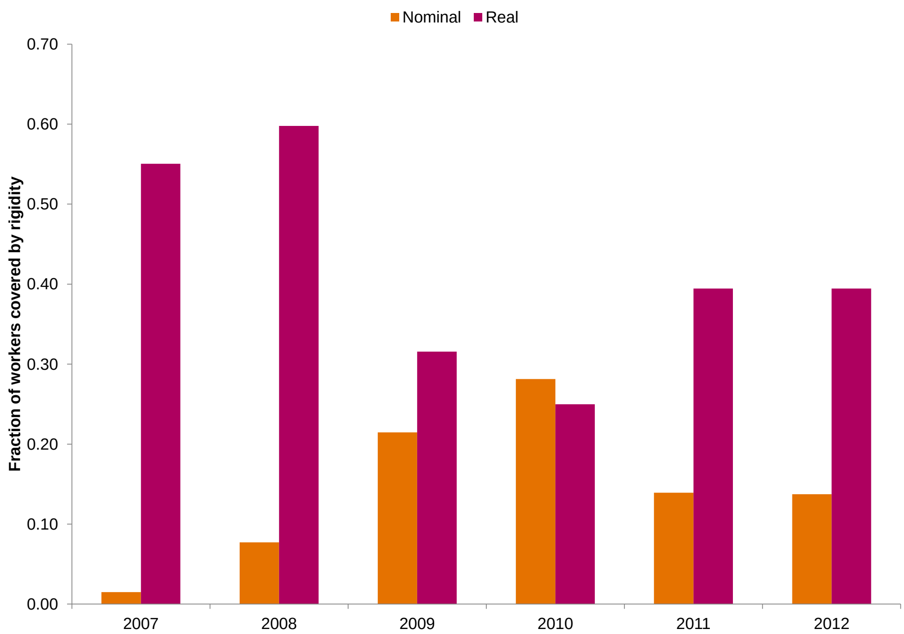
$\hat{\sigma}_{d_t d_{t+1}}$ is defined as

$$
\hat{\sigma}_{d_t d_{t+1}} = \sum_{i=1}^{N_{t,t+1}} \frac{(d_{i,t} - \bar{d}_t)(d_{i,t+1} - \bar{d}_t)}{N_{t,t+1} - 1}. \tag{A.15}
$$

This means only a,$p_{m|e}$ and p_{ne} have to be optimized. The estimated variance-covariance matrix $\hat{\mathbf{\Omega}}_c$ is used as weighting matrix for minimizing the quadratic distance of the described moment conditions.

Appendix B

Model-based IWFP results for the Netherlands according to the original specification



Source: own calculations based on Statistics Netherlands microdata

Figure B.1: The estimated degree of wage rigidity using the original specification of the model-based IWFP method