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Does Downward Nominal Wage Rigidity Dampen Wage Increases?

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18th October 2010

Abstract

Focusing on the compression of wage cuts, many empirical studies find a high degree of downward nominal wage rigidity (DNWR). However, the resulting macroeconomic effects seem to be surprisingly weak. This contradiction can be explained within an intertemporal framework in which DNWR not only prevents nominal wage cuts but also induces firms to compress wage increases. We analyze whether a compression of wage increases occurs when DNWR is binding by applying *Unconditional Quantile Regression* and *Seemingly Unrelated Regression* to a data set comprising more than 169 million wage changes. We find evidence for a compression of wage increases and only very small effects of DNWR on average real wage growth. The results indicate that DNWR does not provide a strong argument against low inflation targets.

Keywords: Downward Nominal Wage Rigidity; Wage Stickiness; Wage Compression; Unconditional Quantile Regression

JEL-classification: E24, E31, J31

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1. Introduction

Concerns about potentially adverse employment effects of low inflation have given rise to a plethora of studies on the extent of downward nominal wage rigidity (DNWR), such as the micro-econometric multi-country studies of Behr and Poetter (2010), Knoppik and Beissinger (2009) and Dickens et al. (2007) or the survey evidence provided by Bewley (1999).[1] These concerns are based on Tobin's (1972) hypothesis that if nominal wages are downwardly rigid a certain amount of positive inflation may be necessary to ease firms' real wage adjustments in response to idiosyncratic shocks ("inflation may grease the wheels of the labor market"). Focusing on the compression of wage cuts, microeconometric studies usually find a high degree of DNWR. However, the resulting macroeconomic effects on aggregate real wages and employment seem to be surprisingly weak, leading Lebow et al. (1999) to speak of a "micro-macro puzzle".

A possible solution to that puzzle has been offered by Elsby (2009), who develops an intertemporal model in which downward wage rigidity arises because nominal wage cuts are followed by sharp decreases in productivity. Wage increases therefore become irreversible to some degree. Firms that increase wages during upswings may find it difficult to reverse their decisions later when the economic environment will possibly deteriorate. Forward-looking firms take the path dependence of wage changes into account when determining the optimal wage policy; they refrain from large wage increases in order to reduce the probability of costly future nominal wage cuts. Moreover, since DNWR raises the wage level inherited from the past, firms do not have to raise wages as much or as often as in a situation without wage rigidity to obtain the profit-maximizing wage level. As a consequence, firms will compress wage increases as well as wage cuts in the presence of DNWR. This leads to the surprising prediction that average real wage growth, and hence aggregate real wages, should not be affected by DNWR, and that the aggregate employment effects should be weak or non-existent.

The contribution of this paper to the literature is twofold. First, we extend the empirical approach of Elsby (2009) by applying Unconditional Quantile Regressions (UQR) to the data, in addition to variants of Elsby's (2009) OLS model specification. The latter only allows the use of aggregate data on the regional level, whereas the application of UQR enables us to take account of the variance and the cross variable covariance in the micro data. Second, we provide an empirical analysis of the effects of inflation on the shape of the real wage change distribution for Germany, a country with stronger labor unions and a higher labor union density than in the US and GB – for which Elsby provides empirical evidence. Our analysis

[1] Dickens et al. (2007) also deal with the extent of real wage rigidities. Holden and Wulfsberg (2008) have carried out a multi-country study on downward nominal wage rigidity using industry data.

provides some insights into whether Elsby's (2009) predictions can be observed in a country that may already be affected by wage compression due to its labour market institutions. In line with the empirical literature on DNWR the analysis focuses on the wage change distribution of job stayers, whereas Elsby's analysis also includes job movers. This inclusion could lead to a systematic relationship between inflation and the compression of the real wage change distribution that has nothing to do with downward nominal wage rigidity. The reason is that during economic upswings inflation often rises, and at the same time more voluntary job changes occur that go hand in hand with real wage increases (see e.g., Cornelißen et al., 2007).

The empirical analysis is undertaken for West-Germany for the period 1975-2007 using the IAB Beschäftigten-Historik (BeH), the Employee History File, of the Institute for Employment Research (IAB) of the German Federal Employment Agency. The BeH comprises the total population gainfully employed and covered by the social security system. After our data selection, the remaining spells enable us to analyze over 169 million earnings changes amounting to more than 5,250,000 earnings changes per year on average. Among the main advantages of this dataset are the sheer wealth of information and the high reliability of the earnings data, which is due to plausibility checks performed by the social security institutions and the existence of legal sanctions for misreporting. In contrast to studies based on compensation data from household surveys, measurement error due to erroneous reporting does not arise in our analysis.

The remainder of the paper is structured as follows. The next section summarizes the key findings of Elsby's (2009) model. Section 3 contains the data description. Section 4 presents our empirical implementation and results as well as a comparison with Elsby's results. Section 5 deals with the macroeconomic implications, and Section 6 concludes.

2. The Model

In this section we explain the main idea of the underlying model and present the key findings needed for the empirical testing.

The main feature of Elsby's (2009) intertemporal model of worker resistance to wage cuts is that wage increases become irreversible to some degree because nominal wage cuts lead to a sharp decrease in productivity. This assumption is based on Bewley's (1999) findings that a key reason for the reluctance to cut nominal wages is the belief that nominal wage reductions could damage worker morale, and that morale is a key determinant of worker productivity. A wage increase will raise productivity, however, a wage cut of the same amount will reduce productivity by a greater amount. Formally, this is captured by an effort function in the spirit of the fair-wage effort hypothesis of Solow (1979) and Akerlof and Yellen (1986), with an additional term reflecting the impact of nominal wage cuts on effort.

$$e = \ln\left(\frac{W}{B}\right) + c\ln\left(\frac{W}{W_{-1}}\right)\mathbf{I}(W < W_{-1}), \qquad (1)$$

where W is the nominal wage, W_{-1} is the lagged nominal wage, $c > 0$ is a parameter varying the productivity costs of a nominal wage cut to the firm, and $\mathbf{I}(\cdot)$ is the indicator function for a nominal wage cut. Real unemployment benefits $b = B/P$ are assumed to be constant over time, where B denotes nominal unemployment benefits and P is the price level. The price level evolves according to $P_t = e^{\pi} P_{t-1}$, where π reflects the inflation rate.

Given the effort function (1), Elsby (2009) considers a discrete-time, infinite-horizon model. In the model price-taking worker-firm pairs maximize the expected discounted value of profits by choosing the nominal wage W_t at each date t. The worker-firms' productivity function is given by $(A/P) \times e$, where A denotes a nominal technology shock. The shock is idiosyncratic to the worker-firm pair, is observed contemporaneously, and acts as the source of uncertainty in the model. The shocks evolve according to a geometric random walk. This has the implication that average nominal productivity rises in line with inflation π and productivity growth μ.

The value of a job in recursive form is given by

$$J(W_{-1}, A) = \max_{W}\left\{A\left[\ln\left(\frac{W}{B}\right) + c\ln\left(\frac{W}{W_{-1}}\right)\mathbf{I}(W < W_{-1})\right] - W + \beta e^{-\pi}\int J(W, A^{'})dF(A^{'} \mid A)\right\}, \qquad (2)$$

where $\beta \in [0,1)$ is the real discount factor of the firm. Lagged values are denoted by the subscript -1, and forward values by a prime. By setting $c = 0$ the model is reduced to a frictionless model. It can be shown that frictionless nominal wages are equal to the nominal shock A, hence wage changes fully reflect changes in productivity.

DNWR changes the shape of the frictionless wage change distribution in two characteristic ways. First, there is a range of values for the nominal shock A, for which the firm finds it optimal not to change the nominal wage. This leads to a spike at zero in the nominal wage change distribution and accordingly to a spike at minus the inflation rate in the real wage change distribution. Second, if the change in A is strong enough and the firm decides to change the nominal wage, the wage change will be compressed relatively to the frictionless case. Not surprisingly, wage cuts are compressed because they imply a discontinuous fall in productivity at the margins. More interestingly, the model predicts that wage increases are compressed as well. One reason is that forward-looking firms take the path dependence of wage changes into account when determining the optimal wage policy; they refrain from large wage increases in order to reduce the probability of costly future nominal wage cuts. Moreover, the firms will in general inherit higher wages from the past. Consequently, firms do not have to increase nominal wages by as much or as often in order to achieve the desired wage level.

Figure 1 shows simulated real wage change distributions for high and low inflation based on the predictions of the theoretical model. One can see that real wage increases are compressed in the case of low inflation.[2]

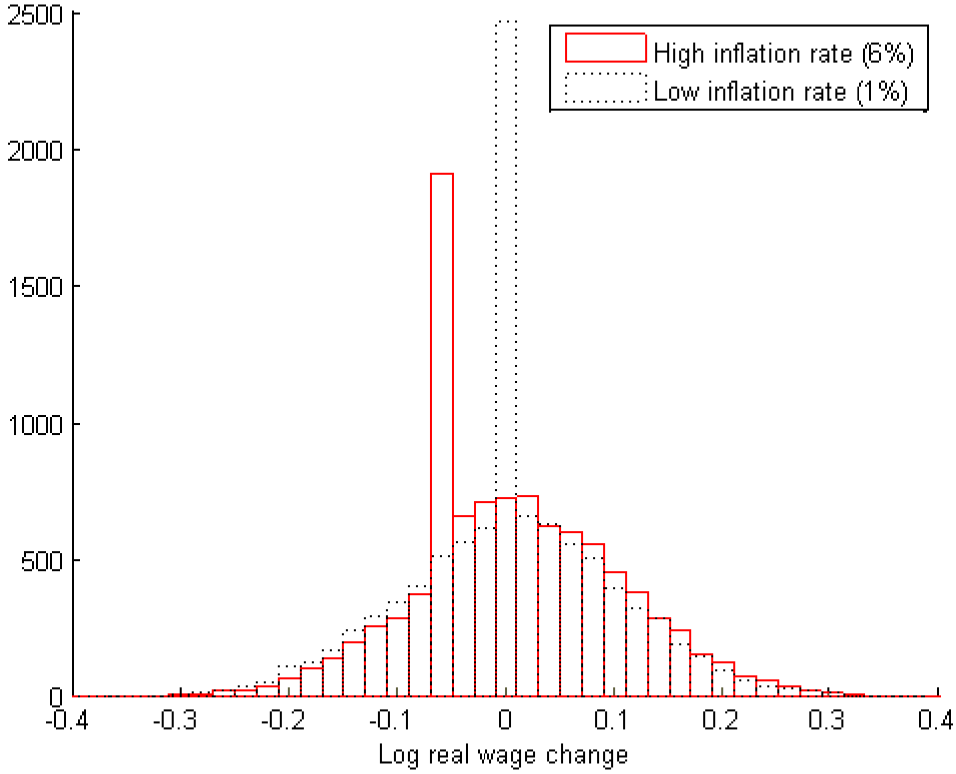

Fig. 1. Figure shows simulated log real wage change distributions after 15 iterations. The distributions have been simulated using Elsby's (2009) model. Own simulation of 10,000 wage changes with DNWR (c = 0.06). Further model settings: 1% productivity growth; β = 0.97.

Notice that in the absence of DNWR a change in the productivity growth rate should lead to a one-to-one shift of the real wage change distribution, whereas a change in the inflation rate should leave the distribution unaltered. In contrast, if DNWR exists, one should observe a

2 In the simulation the rate of productivity growth has been kept constant. Similar effects on the real wage change distribution are obtained if the (average) rate of productivity growth is changed instead of a change in the inflation rate.

systematic relationship between changes in the inflation rate and/or productivity growth rate on the one hand and changes in the shape of the real wage change distribution on the other hand. In the following, we will focus on the impact of the inflation rate on the shape of the real wage change distribution because the inflation rate can be controlled by monetary policy.

The compression of nominal wage changes will have effects on the percentiles of the real wage change distribution. If DNWR is present, the model generates the following predictions about the effect of the inflation rate on the percentiles of the real wage change distribution, depending on whether the percentiles

1. lie below the range of zero nominal wage changes;
2. lie in the range of zero nominal wage changes;
3. lie above the range of zero nominal wage changes.

(1) Nominal wage cuts will be compressed relatively to the frictionless case, because of the implied fall in productivity. The probability that a firm is willing to increase nominal wages will increase as the inflation rate and productivity growth rise. With higher inflation and/or higher productivity growth a firm is more likely to reverse nominal wage cuts in the future. As a result, a firm is less inclined to incur the costs of wage cuts. With higher inflation one should therefore observe fewer and less pronounced nominal wage cuts. The model therefore implies that low percentiles of the real wage change distribution, lying below the range of zero nominal wage change, will rise with the inflation rate and productivity growth.

(2) Because of DNWR a non-negligible range of the percentiles of real wage changes will correspond exactly to zero nominal wage changes and therefore be equal to minus the inflation rate. The model implies that those percentiles of the real wage change distribution fall one-to-one with the inflation rate. With higher inflation firms affected by DNWR are able to achieve reductions in real labor costs without falling back on costly nominal wage cuts. It is in this sense that inflation greases the wheels of the labor market in the presence of DNWR.

(3) In an uncertain world a firm affected by DNWR will also compress nominal wage increases because raising wages increases the risk of costly future nominal wage cuts. If inflation is low, upper percentiles of the wage change distribution will, therefore, be reduced relative to the frictionless case. The probability that a firm wishes to reduce nominal wages will decline when the inflation rate and productivity growth rise. In this case, firms are less likely to cut wages in the future, and no longer need to restrain increases as much as a precaution against future costly nominal wage cuts. On average this should lead to a more than one-to-one increase of the upper percentiles of real wage change distribution with productivity growth as well as to an increase with inflation.

Because of this, one expects the following coefficients in a regression of the percentiles of the log real wage change distribution on the inflation rate and the productivity growth rate as explanatory variables (see Table 1):

Table 1: Predicted effects of the rate of inflation and of productivity growth on the unconditional percentiles of the log real wage change distribution

τ th percentile of the log real wage change distribution (P_τ)	Coefficient on	
	inflation rate	productivity growth
P_τ < minus inflation rate	> 0	> 1
$P_\tau \approx$ minus inflation rate	< 0	attenuates towards zero (< 1)
P_τ > minus inflation rate	> 0	> 1

3. Data

The empirical analysis is undertaken for West-Germany for the period 1975-2007 using the IAB Beschäftigten-Historik (BeH), the Employee History File of the Institute for Employment Research (IAB) of the German Federal Employment Agency. The BeH comprises the total population gainfully employed and covered by the social security system. Not covered are self-employed, family workers assisting in the operation of a family business, civil servants (Beamte) and regular students. For the years 1975 until 2007, the BeH contains information about 72,695,902 people as well as 1,171,326,023 employment spells (IAB Beschäftigten-Historik, 2009). Important advantages of this dataset are the enormous amount of information and the high reliability of the earnings data, which is due to plausibility checks performed by the social security institutions and the existence of legal sanctions for misreporting. In contrast to studies based on compensation data from household surveys measurement error due to erroneous reporting should not arise in our analysis.

The earnings data are right-censored at the contribution assessment ceiling (Beitragsbemessungsgrenze). For employees whose earnings are censored earnings changes cannot be computed. For our analysis we use non-censored earnings spells of male employees from West Germany aged 16 to 65. In line with the literature our analysis is confined to “job stayers”, i.e. employees who have a “stable employment relationship” with an employer. Usually, job stayers are defined as full-time working employees who do not change the employer between two consecutive time periods. We apply a narrower and better suited concept and require that the employee continually exercises the same job at the same employer for at least two consecutive years.[3] In contrast to our data selection Elsby (2009) includes job movers in his analysis. This inclusion could lead to a systematic relationship between inflation and the compression of the wage change distribution that has nothing to do with downward nominal wage rigidity (DNWR). The reason is that during economic upswings inflation usually rises, and at the same time more voluntary job changes occur that go hand in hand with real wage increases (Cornelißen et al., 2007).

After the selection 169 million earnings changes remain in our sample. We are therefore able to analyze an average of more than 5,250,000 earnings changes per year. The sample size is a large advantage in comparison to the data applied in Elsby (2009). His largest data set, the NES for Great Britain, allows him to analyze on average less than 74,000 observations per year. For the US it is less than 24,000 (1,800) observations using the CPS (PSID). A further advantage of the German data is the longer time period of 32 years compared to 21-24 years in Elsby's analysis. A disadvantage of the German data is the fact that we are not able to observe hourly wages, but daily wages. There is also the problem that shifts from part-time to full-time work and vice versa that occur during the course of the year do not lead to a new report of the employer.[4] Since such shifts are much more common for female employees (see e.g., Schäfer and Vogel, 2005), we exclude women from our analysis. This is in contrast to Elsby's analysis in which male and female employees are included.

As inflation rate we use the log change in the Consumer Price Index (CPI) and alternatively the log change in the Producer Price Index (PPI) for Germany. The CPI is more relevant for employees, whereas the PPI is crucial for firms' wage setting. Following Elsby (2009), we measure productivity growth using the observed average regional real wage change. The reason for not directly using a productivity measure is that real wages adjust to changes in productivity with a time lag. We would have to model some kind of error-correction mechanism for the discrepancy between real wage changes and productivity growth. We can avoid these complications by using the average regional real wage change as a proxy variable reflecting the impact of (regional) productivity growth on wages. It is a suitable proxy since according to the theoretical predictions DNWR should have no effect on average wage changes.

Among the other control variables the absolute change in the rate of inflation is included. This is motivated by the hypothesis of Groshen and Schweitzer (1999) that higher inflation volatility yields greater dispersion in relative wages regardless of the existence of DNWR.

[3] The breakdown of occupations is very detailed, but still not every job change leads to a change in the occupation classification. Therefore, some spells of persons who changed the job within a firm may not be excluded. The narrower "same position"-restriction has also been applied by Christofides and Stengos (2001).

[4] A new state is conveyed with the annual report at the end of a year. This state applies for the whole year.

The current and lagged regional unemployment rates are included because DNWR may affect unemployment. The unemployment rates are used to control for changes in the wage change distribution due to workers “leaving” the distribution. Further control variables for the applied regression methods are shown in Table 2. For more details concerning the data and the data selection see Appendix A.

Table 2: Variables for the applied regression methods

	Seemingly Unrelated Regression / OLS Regression	**Unconditional Quantile Regression**
Dependent Variable		
Real wage change	τ th percentile from re-weighted regional log real wage change distribution	Recentered influence function (RIF) of the individual log real wage change
Explanatory Variables		
Inflation rate	Log change in the Consumer Price Index (CPI) for Germany	
	Alternatively: log change in the Producer Price Index (PPI) for Germany	
Productivity growth	Average regional real wage change	
Further Control Variables		
Micro Variables		
Age	Mean age of employees in region	Age
		Age squared
Education	Percentages of employees in region within 7 educational classes	Education class of employee
Foreign nationality	Percentage of employees in region with foreign nationality	Dummy for employee with foreign nationality
Occupation	Percentages of employees in region within 6 occupational fields	Occupation field of the employee
Worker	Percentage of white-collar worker in the region	Dummy for white-collar worker
Regional Variables		
Absolute change in the rate of inflation	Absolute change in the rate of inflation (CPI or PPI)	
Unemployment rate	Current regional unemployment rate	
	Lagged regional unemployment rate	
Dummy Variables		
Year 1984	Before 1984 the inclusion of fringe benefits to notification was voluntary. Since 1984, one-time payments to employees have been subject to social security taxation and are therefore included in the data. This leads to a level effect on the 1983-1984 earning changes. For more details see Appendix A.	
Regions	Dummies for the 10 old West German states (excluding Berlin)	

4. Empirical Implementation and Results

Elsby (2009) uses an OLS regression to estimate the effect of the inflation rate and the average regional real wage change (as proxy for productivity growth) on the percentiles of the real wage change distribution and finds evidence for wage compression for the upper percentiles. A disadvantage of this OLS regression is that only aggregate data at regional level can be used, thereby neglecting the variance and the cross variable covariance in the micro data. First, an identical mean does not imply that the distributions are identical, too. Second, for example, it is possible to observe two regions with the same mean age of the employees and the same composition of the educational classes. Using OLS regression these two regions are identical in terms of age and education. But a closer look could reveal that in one region mainly young employees are highly educated while in the other region mainly older employees are highly educated. Therefore micro data should be used for the analysis wherever possible.

Because of the above mentioned critique we apply two regressions methods. In order to enable a comparison with Elsby's (2009) results, we first apply variants of his OLS approach to our data and estimate the impact of inflation and other variables on the percentiles of the real wage change distribution. Those approaches only include aggregate data on regional level. Second, we apply a new regression method proposed by Firpo, Fortin and Lemieux (2009) – Unconditional Quantile Regression. It allows to use micro data and to estimate the impact of explanatory variables, like inflation, on the percentiles of the unconditional real wage change distribution. The advantage of UQR over OLS is that it takes the whole distribution of the explanatory variables into account.[5] Finally, we shortly compare our results with the results Elsby obtained for the US and GB.

4.1 Impact of Inflation on the Unconditional Percentiles using Seemingly Unrelated Regression

To assess whether the shape of the real wage change distribution varies systematically with the inflation rate because of DNWR, we have to make sure that observed differences in the shape of the distribution are not due to changes in other variables, like age or regional composition of the workforce. To that end we apply the method of DiNardo, Fortin and Lemieux (1996), henceforth "DFL", that enables the estimation of counterfactual (re-weighted) real wage change distributions that would prevail if the distribution of worker characteristics did not change. The worker characteristics for the re-weighted density are age, age squared, class of worker, a dummy for foreign nationality, qualification level and

[5] We also applied Quantile Regression to the data to look at the effects of the inflation rate or of productivity growth on the real wage change distribution *conditional* on the attributes of the employee and conditional on the region where the employee works. The results are shown in Appendix B.

occupational field.[6] The DFL method is useful because it requires no parametric assumptions on the effect of these controls on wage changes.

We use the re-weighted real wage change distributions to calculate the τ^{th} percentile of the distribution for region *r* at time *t* $(P_{\tau,rt})$, with τ = 10, 20, ..., 90. As a first approach we estimate the effect of the inflation rate, π, on $P_{\tau,rt}$ using regressions of the following form:

$$P_{\tau,rt} = \alpha_\tau + \eta_\tau \pi_t + \lambda_\tau \mu_{rt} + \mathbf{z}'_{rt}\varphi_\tau + \varepsilon_{\tau,rt} = \alpha_\tau + \mathbf{x}'_{\tau,rt}\boldsymbol{\beta}_\tau + \varepsilon_{\tau,rt} \tag{3}$$

As inflation rate, π, we alternatively use the log change in the Consumer Price Index (CPI) and the log change in the Producer Price Index (PPI) for Germany. In eq. (3) we take into account that the location of the real wage change distribution for region *r* at time *t* depends on productivity growth μ_{rt} – measured as average regional real wage growth. The vector $\mathbf{z}_{rt}$ contains further control variables shown in Table 2.

Elsby (2009) uses OLS regressions with region-specific dummies - Least Squares Dummy Variable (LSDV) regressions. But since we regress the different percentiles of one single distribution, the residuals are very likely simultaneously correlated across equations. Therefore, we use a LSDV approach within a Seemingly Unrelated Regression (SUR) with small-sample adjustment and weighting by region size:[7]

$$\mathbf{P} = \begin{bmatrix} P_{10,rt} \\ P_{20,rt} \\ \vdots \\ P_{90,rt} \end{bmatrix} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon} = \begin{bmatrix} \mathbf{x}'_{10,rt} & \mathbf{0} & \cdots & \mathbf{0} \\ \mathbf{0} & \mathbf{x}'_{20,rt} & \cdots & \mathbf{0} \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{0} & \mathbf{0} & \cdots & \mathbf{x}'_{90,rt} \end{bmatrix} \begin{bmatrix} \boldsymbol{\beta}_{10} \\ \boldsymbol{\beta}_{20} \\ \vdots \\ \boldsymbol{\beta}_{90} \end{bmatrix} + \begin{bmatrix} \varepsilon_{10,rt} \\ \varepsilon_{20,rt} \\ \vdots \\ \varepsilon_{90,rt} \end{bmatrix} \tag{4}$$

with $\mathbf{x}'_{\tau,rt} = \begin{pmatrix} \mu_{rt} & \pi_t & \mathbf{z}'_{rt} \end{pmatrix}$

The results of the SUR estimates can be found in Table 3.[8] Our results show that the upper tail of the wage change distribution is compressed as a result of DNWR as predicted by the model (see Table 1). The estimated impact of the inflation rate is significantly positive for the 80-90$^{\text{th}}$ percentiles; the coefficients on productivity growth – measured as average regional real

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[6] See DiNardo et al. (1996) or Fortin et al. (2010) for a description of the procedure. We apply the DFL method to each region and as the "base year" we choose the final sample year (2007). The weights are estimated using a probit model according to the Stata ado file provided by Fortin: http://faculty.arts.ubc.ca/nfortin/datahead.html.

[7] We performed "within" Fixed Effects and Random Effects regressions for all percentiles. For each percentile we tested whether or not there are significant differences in the coefficients of the two regressions using Hausman-Tests. The Hausman-Test was rejected for every percentile, therefore we use a Fixed Effects model.

[8] For comparison, the results of a LSDV regression ignoring the contemporaneous correlation of the residuals are documented in Table C1 of Appendix C.

wage change – (significantly) exceed unity for these percentiles. These results are consistent with lower inflation leading to a compression of wage increases.

Table 3: Effects of inflation and productivity growth on the unconditional percentiles of the real wage change distribution

	Consumer Price Index			Productivity growth		
	Coef.	Std.Err.	P>|t|	Coef.	Std.Err.	P>|t|
p10	-0.063	0.027	0.021	0.912†	0.024	0.000
p20	-0.114	0.015	0.000	0.858†	0.013	0.000
p30	-0.082	0.016	0.000	0.927†	0.015	0.000
p40	-0.101	0.021	0.000	0.959†	0.019	0.000
p50	-0.088	0.017	0.000	0.958†	0.016	0.000
p60	-0.043	0.015	0.004	0.987	0.013	0.000
p70	0.005	0.013	0.723	1.004	0.012	0.000
p80	0.047	0.016	0.003	1.024	0.014	0.000
p90	0.091	0.033	0.005	1.057	0.029	0.000

	Producer Price Index			Productivity growth		
	Coef.	Std.Err.	P>|t|	Coef.	Std.Err.	P>|t|
p10	0.007	0.011	0.545	0.945†	0.022	0.000
p20	-0.032	0.006	0.000	0.889†	0.012	0.000
p30	-0.030	0.006	0.000	0.947†	0.013	0.000
p40	-0.069	0.007	0.000	0.952†	0.014	0.000
p50	-0.062	0.006	0.000	0.952†	0.012	0.000
p60	-0.042	0.005	0.000	0.975†	0.011	0.000
p70	-0.014	0.005	0.004	0.991	0.010	0.000
p80	0.017	0.006	0.007	1.018	0.013	0.000
p90	0.061	0.013	0.000	1.069†	0.025	0.000

SUR with small-sample adjustment weighted by region size. Controls: regions, mean age, absolute change in inflation, current and lagged unemployment rate, dummy for the year 1984, percentage of the educational classes, percentage of workers with foreign nationality, percentage of white-collar worker, percentage of the occupational fields. †: coef. for productivity growth significant different from 1 on 5% level.

For reference, Table 3 also reports estimates on the effects of inflation and productivity growth on lower percentiles. Note that the predictions of the model on the coefficients for lower percentiles depend on the position of zero nominal wage change in the distribution of the real wage change distribution (see Table 1).

The results for percentiles in the range of zero nominal wage changes are consistent with the predictions of the model. In our data the spike at zero nominal wage change predominantly appears above the 10^{th} and below the 30^{th} percentile.[9] In this percentile range – in Table 3 represented by the 20^{th} percentile - the coefficients on the inflation rate are significantly negative and the coefficients on productivity growth are significantly below one and attenuate towards zero compared to the coefficients of the 10^{th} and the 30^{th} percentile.

For percentiles that predominantly lie below the range of zero nominal wage changes – in our case the 10^{th} percentile – the model predicts a coefficient of the inflation rate larger than zero. Here the prediction of the model often fails. This may be due to the fact that for 13 years the spike at zero nominal changes lies near the 10^{th} percentile (between the 6^{th} and the 14^{th}

[9] Zero nominal wage changes appear in the range between the 6^{th} and the 37^{th} percentile. For the early years of our data set with higher inflation the spikes predominantly appear in very low percentiles while for later years, with very low inflation, the spikes predominantly appear in higher percentiles of the range. For later years the spike is often observed over more than one percentile. Generally we observe the zero nominal wage change 7 times for percentiles ≤ the 10^{th} percentile, 12 times for the range above the 10^{th} and ≤ the 20^{st} percentile, 24 times in the range above the 20^{th} and ≤ the 30^{st} percentile and 9 times for percentiles above the 30^{th} percentile.

percentile). Using the CPI as inflation rate the coefficient on inflation is significantly negative. Using the PPI the coefficient is positive as predicted by the model, but not significant. The coefficients on productivity growth are higher than those of the 20th percentiles, but they do not rise above unity as predicted by the model.

4.2 Impact of Inflation on the Unconditional Percentiles using Unconditional Quantile Regression

In the following we apply the Unconditional Quantile Regression (UQR) approach proposed by Firpo, Fortin and Lemieux (2009) to estimate the impact of explanatory variables, like inflation, on the percentiles of the *unconditional* real wage change distribution taking into account the variance and cross variable covariance in the micro data.[10] A standard Quantile Regression (Koenker/Bassett 1978; Koenker 2005) is only able to observe the effects of inflation on the *conditional* percentiles of the real wage change distribution. Wage changes that correspond to a certain conditional percentile can be distributed over the entire observed (unconditional) wage change distribution. The UQR, however, allows to estimate the impact of changes in the distribution of explanatory variables, $\mathbf{X}$, on the marginal percentiles of the dependent variable, Y. A further advantage of applying UQR to the data is that we do not need to apply the DFL method in the first step to estimate counterfactual wage change distributions.

To estimate the average marginal effect $E[d\Pr[Y > P_\tau \mid \mathbf{X}]/d\mathbf{X}]$ Firpo et al. (2009) propose, inter alia, a *Recentered Influence Function OLS* (RIF-OLS) regression.[11] This regression provides consistent estimates if $\Pr[Y > P_\tau \mid \mathbf{X} = x]$ is linear in x. In case of quantiles the conditional expectation of the recentered influence function $E[RIF(Y; P_\tau, F_Y) \mid \mathbf{X}]$ can be viewed as an Unconditional Quantile Regression.

The RIF-OLS consists of regressing the (recentered) influence function RIF of the outcome variable Y for the τ^{th} percentile P_τ on the explanatory variables $\mathbf{X}$ by OLS. The RIF is computed by estimating the sample percentile P_τ and the density of the outcome variable $\hat{f}_Y(\cdot)$, using kernel (or other) methods: $R\hat{I}F(Y; \hat{P}_\tau) = \hat{c}_{1,\tau} \cdot \mathbf{I}(Y > \hat{P}_\tau) + \hat{c}_{2,\tau}$, where $\mathbf{I}(\cdot)$ is an indicator function, $\hat{c}_{1,\tau} = 1/f_{Y(P_\tau)}$, $f_{Y(P_\tau)}$ is the density of Y evaluated at P_τ and $\hat{c}_{2,\tau} = P_\tau - c_{1,\tau} \cdot (1-\tau)$. We follow Firpo et al. and use a kernel density estimator $\hat{f}_Y(\hat{P}_\tau) = \frac{1}{N \cdot b} \cdot \sum_{i=1}^{N} \kappa_Y\left(\frac{Y_i - \hat{P}_\tau}{b}\right)$, where $\kappa_Y(\cdot)$ is a kernel function, and $b > 0$ denotes the scalar

[10] The „unconditional percentiles“ are the percentiles of the marginal distribution of the outcome variable.
[11] For a short introduction see also Fortin et al. (2010).

bandwidth.[12] We make use of the RIF-OLS and regress the percentile-transformed individual log real wage change on $\mathbf{X} = \left(\mu_{rt} \quad \pi_t \quad \mathbf{z}_{irt}^{'}\right)$. The vector $\mathbf{z}$ contains the control variables on the individual level wherever possible (see Table 2). To estimate the density of the individual log real wage change we use a Gaussian kernel.[13] The bandwidth b is set to the 'optimal' width.[14] For the regression we use a ten percent stratified sample of our data.[15] The results for the UQR can be found in Table 4.

The UQR shows significantly positive coefficients for the inflation rate for the 90th percentiles. These results are consistent with lower inflation leading to a compression of wage increases - the upper tail of the unconditional wage change distribution is compressed as a result of DNWR. However, only very high wage increases are compressed. In contrast, as has been shown above, for the SUR the coefficients for the 80th – 90th percentiles of the inflation rate are significantly positive. This points to an overestimation of the compression of wage increases using SUR.

Table 4: Effects of inflation and productivity growth on the unconditional percentiles of the real wage change distribution

	Consumer Price Index			Productivity growth		
	Coef.	Std.Err.	P>|t|	Coef.	Std.Err.	P>|t|
p10	-0.043	0.004	0.000	0.862†	0.003	0.000
p20	-0.148	0.002	0.000	0.716†	0.002	0.000
p30	-0.152	0.002	0.000	0.813†	0.002	0.000
p40	-0.136	0.002	0.000	0.862†	0.002	0.000
p50	-0.142	0.001	0.000	0.949†	0.001	0.000
p60	-0.165	0.002	0.000	0.993†	0.002	0.000
p70	-0.125	0.002	0.000	0.952†	0.002	0.000
p80	-0.037	0.003	0.000	0.950†	0.003	0.000
p90	0.068	0.005	0.000	0.979†	0.005	0.000

	Producer Price Index			Productivity growth		
	Coef.	Std.Err.	P>|t|	Coef.	Std.Err.	P>|t|
p10	0.036	0.002	0.000	0.930†	0.003	0.000
p20	-0.002	0.001	0.033	0.778†	0.002	0.000
p30	-0.069	0.001	0.000	0.810†	0.002	0.000
p40	-0.066	0.001	0.000	0.849†	0.001	0.000
p50	-0.081	0.001	0.000	0.911†	0.002	0.000
p60	-0.087	0.001	0.000	0.961†	0.002	0.000
p70	-0.055	0.001	0.000	0.935†	0.002	0.000
p80	-0.010	0.001	0.000	0.939†	0.003	0.000
p90	0.061	0.002	0.000	0.991†	0.004	0.000

Unconditional Quantile Regression. Controls: region dummies, age, age squared, absolute change in inflation, current and lagged unemployment rate, dummy for the year 1984, educational class, dummy for worker with foreign nationality, occupational fields, dummy for white-collar worker. Bootstraped standard errors. 50 replications. †: coef. for productivity growth significant different from 1 on 5% level.

For reference, Table 4 also reports estimates on the effects of inflation and productivity growth on lower percentiles. Note that the predictions of the model on the coefficients for

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12 The influence function $IF(Y;\nu,F_Y)$ of a distributional statistic $\nu(F_Y)$ represents the influence of an individual observation on that distributional statistic. Adding back the statistic $\nu(F_Y)$ to the IF yields what Firpo et al. (2009) call the recentered influence function (RIF). Therefore for the τ^{th} percentile the $RIF(Y;P_\tau,F_Y) = P_\tau + IF(Y;P_\tau,F_Y) = P_\tau + (\tau - \mathbf{I}(Y > P_\tau))/f_Y(P_\tau)$.

13 For the RIF-OLS we used the Stata ado file provided by Fortin: http://faculty.arts.ubc.ca/nfortin/datahead.html.

14 The ‚optimal' width is the width that would minimize the mean integrated squared error if the data were Gaussian and a Gaussian kernel were used. So it is not optimal in a global sense.

15 The sample has been stratified by region, age, foreign nationality, worker class, occupational field and year.

lower percentiles depend on the position of the zero nominal wage change in the distribution of the real wage change distribution (see Table 1). In our data the spike at the zero nominal wage change predominantly appears between the 10^{th} and the 30^{th} percentile. For an overview over the distribution of the position of the zero nominal wage change see footnote 9.

The results for the percentiles in the range of zero nominal wage changes are consistent with the predictions of the model that coefficients on the inflation rate are significantly negative and the coefficients on productivity growth are below one and attenuate towards zero. In the percentile range above the 10^{th} and below the 30^{th} percentiles – in Table 4 represented by the 20^{th} percentile - the coefficients on the inflation rate are significantly negative and the coefficients on productivity growth are significantly below one and attenuate towards zero compared to the coefficients of 10^{th} and the 30^{th} percentile.

For percentiles below the range of zero nominal wage changes the model predicts coefficients of the inflation rate larger than zero. For those percentiles the results of the UQR fit the predictions of the model better than the results of the SUR. Using the CPI as inflation rate, the coefficient for inflation for the 10^{th} percentile is significantly negative but smaller in absolute value than for the SUR. Using the PPI as inflation, the coefficients of the inflation rate for the 10^{th} percentile are significantly positive. Using SUR we only find a non-significantly positive coefficient for the 10^{th} percentile. This points to an underestimation of the compression of the left tail of the wage change distribution using SUR.

As for productivity growth - measured as the average regional wage change - we find coefficients that are very similar to those obtained using SUR. The coefficients are highest for very high percentiles and the coefficients for the 10^{th} percentiles are higher than for the 20^{th} percentiles. However, the coefficients for very high percentiles do not rise above unity.

4.3 Comparison with results for the US and the UK

Elsby (2009) analyzes whether a compression of wage increases can be found for the US and GB. He uses Ordinary Least Squares regressions with region-specific dummies - a Least Squares Dummy Variable regression - to explain variations in the τ^{th} percentile of the DFL re-weighted real wage growth distribution by the inflation rate, average regional wage change rate (as proxy for productivity growth) and various control variables. This approach is similar to our Seemingly Unrelated Regression introduced in Section 4.2.

For the empirical analysis Elsby (2009) uses data taken from the New Earnings Survey (NES, 1975-1999) for the UK and data taken from the Panel Study of Income Dynamics (PSID, 1971-1992) and the Current Population Survey (CPS, 1979-2002) for the US.

The results are similar to the results for Germany. They provide evidence that as a result of DNWR the upper tail of the real wage change distribution is compressed. For the three data sets the estimated impact of inflation is positive for the 70-90th percentiles and often significant. The coefficients on productivity growth exceed unity for these upper percentiles of the real wage change distribution and are strongly significant.

For the range of zero nominal wage change the coefficients on inflation are negative, and the coefficients on productivity growth attenuate towards zero for all these percentiles. For percentiles below the range at zero nominal wage changes the effect of higher inflation is diminishing – but not significantly positive. Here the prediction of the model fails as for Germany. The coefficient on average regional wage change rises above unity using CPS and NES data.

5. Macroeconomic Implications

In this section we look at the effect of DNWR on average real wage growth and compare the estimated effects using the predictions from the SUR and the UQR. According to the underlying theoretical model, downward nominal wage rigidity (DNWR) should have no effect on average real wage growth and hence on the average real wage level. Previous empirical studies, however, which neglected the compression of wage increases, report positive estimates on the effects of DNWR on average real wage growth (Card and Hyslop, 1997) or the average real wage level (Knoppik and Beissinger, 2003).

In the previous section we showed that wage increases in Germany are compressed when inflation is low. This compression should dampen the so-called "wage sweep-up" effect of DNWR and could even completely annihilate any effect of DNWR on average real wage growth. In order to quantify the impact of DNWR on real wage growth, we estimate the average log real wage change when inflation is low (π_L) and average log real wage change when inflation is high (π_H) and calculate $\hat{\lambda}$, the difference of the estimates. If DNWR has no effect on average real wage growth, $\hat{\lambda}$ should be zero:

$$\hat{\lambda} = \hat{\mathrm{E}}(\Delta \ln w \mid \pi_L, \mu, \mathbf{z}) - \hat{\mathrm{E}}(\Delta \ln w \mid \pi_H, \mu, \mathbf{z}). \tag{5}$$

We estimate the expected average log real wage change using the predictions from the Seemingly Unrelated Regression (SUR) and the Unconditional Quantile Regression (UQR) from section 4. For the calculations we use the fact that the mean of a random variable may be expressed as a simple average of its percentiles.

As for the SUR, we conduct the regression for 99 percentiles. We then use the results to simulate 99 percentiles of the real wage change distribution for a given inflation rate π for each region. Finally we calculate the region size weighted means for the 99 percentiles $P_\tau \mid \pi$.

As for the UQR, we estimate the effect of inflation for the $\tau = 1,2,..,99$ percentiles of the real wage change distribution. We then use the results to simulate 99 real wage change distributions for a given inflation rate π. Finally we use the τ^{th} simulated distribution to calculate the τ th percentile $P_\tau \mid \pi$.

We apply these procedures for the SUR and the UQR for low inflation π_L as well as for high inflation π_H, and then calculate $\hat{\lambda}$ using the predicted percentiles P_τ, for $\tau = 1,2,...,99$. Hence, $\hat{\lambda} \approx \left(\sum_{\tau=1}^{99} P_\tau \mid \pi_L - \sum_{\tau=1}^{99} P_\tau \mid \pi_H \right) \Big/ 99$.

We use a value for π_L equal to 1% and a value for π_H equal to 6%.[16] Since we estimate $\hat{\lambda}$ using a difference in inflation of five percentage points, we can interpret $\hat{\lambda}/5$ as the average change in average real wage growth caused by a decrease in inflation by one percentage point. According to the results shown in Table 5, a decrease in inflation by one percentage point causes an average increase of real wage growth between 0.003% and 0.060%. Our results, using the PPI as inflation rate, are in line with Elsby's (2009) results: for the US a decrease in inflation by one percentage point causes an average increase of real wage growth in the range of 0.002%-0.008% and for the UK of 0.001%. However, using the CPI as inflation, as Elsby does, our results show stronger effects on average real wage growth. Still, all results indicate that the effects of DNWR in combination with low inflation on average real wage growth, and hence on aggregate real wages, are quite small.

Table 5: Increase of the average real wage growth due to a decrease in inflation

Regression method	Average log real wage change caused by a decrease in inflation by 1 percentage point $(\hat{\lambda}/5)$
SUR_{CPI}	0.013%
SUR_{PPI}	0.003%
UQR_{CPI}	0.060%
UQR_{PPI}	0.003%

Unfortunately, a comparison with results from previous studies (e.g., Card and Hyslop, 1997; Knoppik and Beissinger, 2003) is not possible. Those studies use a counterfactual wage change distribution - a distribution that would prevail if DNWR would not bind - to calculate

[16] These inflation rates lie in the range of observed inflation rates during the sample period, using both the CPI and the PPI as inflation rate (see Table A2).

the wage sweep-up.[17] According to our results, the identification of a counterfactual wage change distribution is not possible because the whole distribution is affected by DNWR. Hence, we cannot ascertain by how much previous studies overestimate the effect of DNWR on average real wage change. However, we certainly know that they do overestimate it.

To get an insight into the effects of inflation on the amount of real wage cuts and increases we estimate $\mathrm{E}(\Delta \ln w \mid \pi)$ for negative and for positive real wage changes (see Table 6).[18] The results confirm that with low inflation a compression of wage increases takes place – the expected real wage increases during low inflation are smaller than the expected real wage increases during high inflation. With rising inflation the expected real wage increases get larger, but less people experience a real wage increase. For example, the results for the UQR using the CPI as inflation rate show that for low inflation 59% of the workers experience a real wage increase while for high inflation only 55% experience a real wage increase. However, in the latter case the wage increase is more pronounced. In contrast, for low inflation only 40% of the worker experience a real wage cut while for high inflation 44% experience a real wage cut. It is in this sense that inflation greases the wheels of the labor market in the presence of DNWR.

Table 6: Conditional expected real wage change for negative and for positive real wage changes

Regression method	$\pi = \pi_L$		$\pi = \pi_H$	
	$\mathrm{E}(\Delta \ln w \mid \Delta \ln w < 0)$	$\mathrm{E}(\Delta \ln w \mid \Delta \ln w \geq 0)$	$\mathrm{E}(\Delta \ln w \mid \Delta \ln w < 0)$	$\mathrm{E}(\Delta \ln w \mid \Delta \ln w \geq 0)$
SUR_{CPI}	-3.440% (33)	4.224% (66)	-3.208% (38)	4.599% (61)
SUR_{PPI}	-3.411% (34)	4.300% (65)	-3.134% (37)	4.481% (62)
UQR_{CPI}	-5.120% (40)	8.651% (59)	-5.036% (44)	9.048% (55)
UQR_{PPI}	-5.249% (40)	8.668% (59)	-4.881% (43)	9.108% (56)

The numbers in brackets show how many percentiles are considered calculating the expected value.

[17] Knoppik and Beissinger (2003) using the IABS from the Institute for Employment Research - a 1% random sample drawn from the German social-security accounts – for the years 1975-1995, estimate at zero inflation a sweep-up range from 0.3 to 0.4 additional percentage points of individual expected real wage growth due to wage rigidity. Cornelißen and Hübler (2008) using the German Socio-Economic Panel (GSOEP) for the years 1984-2004, estimate that downward wage rigidity increases real wage growth by 3.4 to 4.9 percentage points.

[18] Specifically, we estimate

$$\mathrm{E}(\Delta \ln w \mid \pi_L, \Delta \ln w < 0) = \left(\sum_{\tau=1}^{n} P_\tau \mid \pi_L\right) \Big/ n, \quad \mathrm{E}(\Delta \ln w \mid \pi_L, \Delta \ln w \geq 0) = \left(\sum_{\tau=n+1}^{99} P_\tau \mid \pi_L\right) \Big/ (99-n)$$

$$\mathrm{E}(\Delta \ln w \mid \pi_H, \Delta \ln w < 0) = \left(\sum_{\tau=1}^{m} P_\tau \mid \pi_H\right) \Big/ m, \quad \mathrm{E}(\Delta \ln w \mid \pi_H, \Delta \ln w \geq 0) = \left(\sum_{\tau=m+1}^{99} P_\tau \mid \pi_H\right) \Big/ (99-m).$$

We also estimate $E(\Delta \ln w \mid \pi)$ for negative and positive nominal wage changes (see Table 7).[19] The results show that, as expected, with high inflation one observes less nominal wage cuts. For example, the results for the UQR with the CPI as inflation rate show that 33% of the workers experience a nominal wage cut when inflation is low, while with high inflation only 13% experience a nominal wage cut.

Table 7: Conditional expected real wage change for negative and for positive nominal wage changes

Regression method	$\pi = \pi_L$		$\pi = \pi_H$	
	$E(\Delta \ln w \mid \Delta \ln w < -\pi)$	$E(\Delta \ln w \mid \Delta \ln w \geq -\pi)$	$E(\Delta \ln w \mid \Delta \ln w < -\pi)$	$E(\Delta \ln w \mid \Delta \ln w \geq -\pi)$
SUR_{CPI}	-4.723% (23)	3.604% (76)	-9.154% (6)	2.296% (93)
SUR_{PPI}	-4.631% (24)	3.662% (75)	-9.234% (6)	2.336% (93)
UQR_{CPI}	-6.111% (33)	7.686% (66)	-11.105% (13)	4.889% (86)
UQR_{PPI}	-6.247% (33)	7.691% (66)	-11.427% (12)	5.027% (87)

The numbers in brackets show how many percentiles are considered calculating the expected value.

6. Summary and Conclusions

The evidence presented in this paper indicates that in times of low inflation downward nominal wage rigidity (DNWR) not only hinders wage cuts but also leads to a compression of wage increases. If the latter effect is taken into account, DNWR has a negligible effect on average real wage growth, and hence on aggregate real wages.

The empirical analysis has been undertaken for West-Germany for the period 1975-2007 using the IAB Beschäftigten-Historik (BeH), the Employee History File of the Institute for Employment Research (IAB) of the German Federal Employment Agency. In line with the literature our analysis has been confined to “job stayers”, i.e. full-time employees who continually exercise the same job at the same employer for at least two consecutive years. After our data selection we were still able to analyze about 169 million earnings changes, i.e. an average of more than 5,250,000 earnings changes per year. The huge sample size and the reliable earnings data are great advantages for our analysis of the impact of DNWR on the shape of the real wage change distribution.

[19] Specifically, we estimate

$$E(\Delta \ln w \mid \pi_L, \Delta \ln w < -\pi_L) = \left(\sum_{\tau=1}^{n} P_\tau \mid \pi_L \right) \Big/ n, \quad E(\Delta \ln w \mid \pi_L, \Delta \ln w \geq -\pi_L) = \left(\sum_{\tau=n+1}^{99} P_\tau \mid \pi_L \right) \Big/ (99-n)$$

$$E(\Delta \ln w \mid \pi_H, \Delta \ln w < -\pi_H) = \left(\sum_{\tau=1}^{m} P_\tau \mid \pi_H \right) \Big/ m, \quad E(\Delta \ln w \mid \pi_H, \Delta \ln w \geq -\pi_H) = \left(\sum_{\tau=m+1}^{99} P_\tau \mid \pi_H \right) \Big/ (99-m).$$

Applying Seemingly Unrelated Regression (SUR) to the percentiles of the log real wage change distribution at the regional level, we have shown that in Germany a compression of wage increases takes place due to DNWR – wage increases are compressed when inflation is low. Because the SUR approach does not consider the variance and the cross variable covariance of the micro data, we have also applied Unconditional Quantile Regression (UQR). This allows to estimate the impact of changing the distribution of explanatory variables on the marginal percentiles of the dependent variable. Using UQR we estimated the impact of inflation on the percentiles of the unconditional real wage change distribution. The results confirm a compression of wage increases due to DNWR. But compared to the SUR estimates less percentiles of the wage change distribution are affected. This points to an overestimation of the compression of wage increases using SUR.

As for the macroeconomic implications of DNWR we find that a decrease in inflation of one percentage point only causes an average increase in real wage growth between 0.003% and 0.060%. These results indicate that DNWR does not provide a strong argument against low inflation targets.

The results can also be used to evaluate different approaches to analyze DNWR in micro data. Our empirical results show that low inflation in combination with DNWR also affects the upper tail of the wage change distribution. As a consequence, approaches such as the normality approach by Borghijs (2001) and the symmetry approach by Card and Hyslop (1997) that assume a symmetric counterfactual wage change distribution and infer the shape of the lower tail of the counterfactual using the upper part of the wage change distribution are seriously flawed. Also other approaches are challenged, like the earnings-function approach by Altonji and Devereux (2000), the histogram-location approach by Kahn (1997), or the approach based on the generalized hyperbolic distribution by Behr and Pötter (2010). They do not assume symmetry of the unconditional counterfactual wage change distribution, but they also assume that DNWR does not affect higher percentiles of the real wage change distribution - an assumption which is challenged by our empirical results.

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Appendix A: Data Selection and Description

For our analysis we only use the earning spells of male employees from West Germany[20] aged 16 to 65. We distinguish between white-collar workers and blue-collar workers. The workers must be subject to social security without particular tokens and being gainfully employed in the same occupation by the same employer throughout the year for at least two consecutive years. The earnings are right-censored at the contribution assessment ceiling (Beitragsbemessungsgrenze). For employees whose earnings are censored the earnings changes cannot be computed correctly. Since the monthly income is censored too, it is possible that yearly earnings are below the contribution assessment ceiling, even if several monthly earnings are censored. This causes some noise for earnings hardly below the contribution assessment ceiling. Therefore earnings spells above 0.96 times the contribution assessment ceiling of the compulsory pension insurance scheme are dropped.

We also control for further employment spells. If a person has more than one employment spell liable to social security – regardless of full- or part-time – we drop the employment spell(s) of that person for the particular year. Still, there are some implausibly high growth rates of (annual) earnings – up to 260 percent. Until 1999 these are concentrated mainly in the group of employees younger than 25 years. This is because not every change in an employment relationship leads to a new spell. For example, until 1999 the BeH item 'class of worker' contains only the last status of the particular year. If a person ends an apprenticeship in the middle of a year, and then is gainfully employed by the same employer for the rest of the year as well as the next year, we will observe the person as being gainfully employed two years in row. Given that after the apprenticeship the respective person is typically earning more than double the previous income, an implausibly high growth rate of annual earnings is observed. To make sure that this and other effects are not at work in our data, we only analyze (annual) wage changes that are higher than the one percent percentile and lower than the 99 percent percentile.

After the selection, the remaining spells comprise 50,575,416 salary changes of white-collar workers as well as 118,593,371 wage changes of blue-collar workers (see Table A1).

[20] Except (West) Berlin.

Table A1: Earnings spells, and observable earnings changes for the BeH and our datasets

Year	Employee History File (BeH) Source: IAB Beschäftigten-Historik (BeH) V08.01, Nürnberg 2009, Tab. 3.4, pp. 13-14.							Dataset for white-collar workers (job stayers)		Dataset for blue-collar workers (job stayers)	
	total BeH			white-collar workers		blue-collar workers					
	Number of spells	**Number of persons**	**Number of new persons**	**Number of spells**	**% of all BeH spells**	**Number of spells**	**% of all BeH spells**	**Observable salary changes** to the previous year	**% of all white-collar workers spells**	**Observable wage changes** to the previous year	**% of all blue-collar workers spells**
1975	25,477,714	22,229,687	22,229,687	8,017,135	31.47	13,115,611	51.48	-------------	-------	-------------	-------
1976	26,312,435	22,027,301	1,821,120	8,162,966	31.02	13,588,660	51.64	1,223,461	14.99	4,001,617	29.45
1977	26,536,964	22,268,246	1,524,711	8,326,823	31.38	13,423,461	50.58	1,339,689	16.09	4,008,105	29.86
1978	26,582,142	22,280,456	1,422,128	8,504,452	31.99	13,125,102	49.38	1,455,036	17.11	3,987,076	30.38
1979	27,735,013	23,050,680	1,519,340	8,741,313	31.52	13,666,833	49.28	1,549,174	17.72	4,026,094	29.46
1980	27,915,481	23,368,670	1,447,888	8,958,331	32.09	13,641,632	48.87	1,550,299	17.31	4,074,915	29.87
1981	27,446,754	23,465,968	1,234,982	9,062,261	33.02	13,059,120	47.58	1,613,492	17.80	4,229,974	32.39
1982	26,601,318	23,174,161	1,115,916	8,912,796	33.51	12,293,271	46.21	1,724,945	19.35	4,267,181	34.71
1983	25,999,555	22,761,297	1,084,306	8,785,081	33.79	11,786,115	45.33	1,823,678	20.76	4,260,338	36.15
1984	26,649,448	22,892,553	1,145,787	8,811,489	33.06	12,226,538	45.88	1,652,739	18.76	4,057,593	33.19
1985	26,704,365	22,781,837	1,091,527	8,759,642	32.80	12,232,551	45.81	1,541,769	17.60	3,966,506	32.43
1986	27,541,879	23,436,642	1,119,212	9,256,438	33.61	12,326,805	44.76	1,539,611	16.63	4,014,362	32.57
1987	28,116,787	23,677,568	1,074,500	9,554,798	33.98	12,439,379	44.24	1,555,887	16.28	4,018,113	32.30
1988	28,698,344	23,786,816	1,033,231	9,882,373	34.44	12,667,343	44.14	1,587,020	16.06	3,988,695	31.49
1989	29,822,255	24,267,501	1,199,883	10,322,363	34.61	13,178,397	44.19	1,587,684	15.38	3,961,452	30.06
1990	31,784,818	25,217,847	1,645,845	10,910,750	34.33	14,143,744	44.50	1,517,988	13.91	3,815,151	26.97
1991	37,527,796	30,390,685	6,141,237	11,316,503	30.15	14,230,801	37.92	1,485,069	13.12	3,912,383	27.49
1992	39,806,357	32,367,400	4,452,503	14,526,173	36.49	17,151,872	43.09	1,518,998	10.46	4,086,827	23.83
1993	38,726,145	31,468,111	1,258,045	14,288,414	36.90	16,307,187	42.11	1,559,944	10.92	4,040,428	24.78
1994	37,109,938	30,765,834	1,150,297	13,658,194	36.80	15,413,334	41.53	1,678,306	12.29	3,993,359	25.91
1995	37,428,190	30,718,658	1,158,163	13,808,067	36.89	15,391,415	41.12	1,704,648	12.35	3,872,681	25.16
1996	36,116,981	30,284,347	1,096,866	13,279,672	36.77	14,530,125	40.23	1,695,637	12.77	3,759,385	25.87
1997	36,708,737	30,034,750	1,224,453	13,221,938	36.02	14,277,362	38.89	1,755,706	13.28	3,765,959	26.38
1998	37,126,961	30,696,402	1,485,883	13,559,574	36.52	13,878,339	37.38	1,716,299	12.66	3,620,074	26.08
1999	45,866,082	35,023,973	2,979,728	14,432,989	31.47	14,799,245	32.27	1,582,533	10.96	3,311,996	22.38
2000	48,046,644	35,989,747	1,700,270	14,635,674	30.46	15,064,596	31.35	1,538,716	10.51	3,222,105	21.39
2001	48,957,095	36,063,811	1,421,173	15,132,476	30.91	15,157,937	30.96	1,479,744	9.78	3,057,588	20.17
2002	47,356,880	35,459,833	1,185,798	14,927,452	31.52	14,240,501	30.07	1,422,480	9.53	2,906,075	20.41
2003	50,878,383	35,163,454	1,142,687	14,850,117	29.19	14,130,373	27.77	1,450,294	9.77	2,901,505	20.53
2004	47,152,731	35,076,422	1,105,978	14,314,460	30.36	13,370,424	28.36	1,650,762	11.53	2,889,431	21.61
2005	46,250,593	34,574,481	1,092,777	13,542,098	29.28	12,957,363	28.02	1,710,424	12.63	2,920,200	22.54
2006	47,148,366	34,856,424	1,154,210	13,559,054	28.76	13,237,171	28.08	1,759,427	12.98	2,907,775	21.97
2007	49,182,872	35,427,149	1,235,771	14,326,287	29.13	13,710,683	27.88	1,603,957	11.20	2,748,428	20.05
Sum	1,171,326,023	---------------	72,695,902	382,348,153	32.64	454,763,290	38.82	50,575,416	13.23	118,593,371	26.08

For each employee we have the following information:

Gross annual earnings:

- salary: gross annual salary of a full-time white-collar worker
- wage: gross annual wage of a full-time worker

The earnings are right-censored at the contribution assessment ceiling (Beitragsbemessungsgrenze). Spells with censored earnings, as well as spells with earnings higher than 0.96 times the contribution assessment ceiling of the compulsory pension insurance scheme, are dropped. The lower limit of earnings is given by the earnings limit for "marginal" part-time workers/fringe workers (Geringfügigkeitsgrenze; see Table A2). These workers are not included in the BeH.

The BeH does not allow separating fringe benefits from "regular" earnings. This is important because before 1984 the inclusion of fringe benefits to notification was voluntary. Since 1984, one-time payments to employees have been subject to social security taxation and are therefore included in the data. This leads to a level effect on the 1983-1984 (log) earnings changes. However, observations before and after 1984 should be valid. If some employers reported fringe benefits before 1984 and other did not, it is very likely that employers were usually consistent in their reporting behaviour.

Gross average daily earnings:

- gross average daily salary of a full-time white-collar worker
- gross average daily wage of a full-time blue-collar worker

The BeH contains no data on hours worked except for information about part-time or full-time employment. Therefore, it is not possible to compute hourly earnings. Since we cannot observe changes in the working time – as long as the threshold for part-time employment is not crossed –we sometimes observe implausibly high growth rates of (annual) earnings.

Using gross annual earnings and the duration of the employment spell, we calculate gross average daily earnings. Since white-collar workers are being paid the same salary every month – irrespective of the number of working days – we calculate the gross average daily salary for a 365-day year. For workers we use the exact duration of the employment spell to calculate the gross average daily wages. To avoid any contamination with working time effects, only full-time employment spells are included.

Duration of employment:

The duration of employment is not consistent with the actual days worked, but represents the duration of the employment contract liable to social security. To make sure that a person is employed all the year, we drop all spells with durations of employment of less than 365 days.

Employment relationship:

The BeH contains 32 classifications for employment relationships – such as trainees, insured artistes and publicists and employees in partial retirement. We only keep employees subject to social security without particular tokens.

Class of worker:

The BeH contains eight classes of workers: (1) trainees, (2) workers, (3) skilled workers[21], (4) master craftsmen and foremen[22], (5) white-collar workers, (6) home workers, (7) people with less than 18 weekly hours of work, and (8) people with 18 and more weekly hours of work but not fully employed.

We drop all classes except of 'white-collar workers', 'workers' and 'skilled workers'. The two latter classes are combined to the class 'blue-collar workers'.

Occupational classification:

This variable describes the field of an employee's occupational specialization. The BeH covers 86 occupation groups containing 328 occupations. These groups are use to control for job stayer. They are subsumed to six occupational fields which are used in the regressions.

Qualification level of an employee:

This variable includes eight categories: (1) no formal education, (2) lower secondary school and intermediate (secondary) school without vocational qualification, (3) lower secondary school and intermediate (secondary) school with vocational qualification, (4) upper secondary school examination without vocational qualification, (5) upper secondary school examination with vocational qualification, (6) post-secondary technical college degree, (7) university degree, and (8) no classification applicable.

The qualification level 'no classification applicable' is subsumed to 'no formal education'.

Age of a person:

Age a person is turning in the particular year – only spells from persons aged 16 to 65 are kept.

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[21] The class also contains master craftsmen and foremen (Bender et al., 1996).

[22] Persons in this class are employed as blue-collar or white-collar workers.

Further data:

Inflation:

As inflation we use two variables:

- Change of the Consumer Price Index (CPI) for Germany to the previous year (see Table A2). We interlinked the CPI (available for 1995-2007) with the cost-of-living index of all private households for West Germany (available for 1962-1999).
- Change of the Producer Price Index for Germany to the previous year (see Table A2).

Table A2: Contribution assessment ceiling for Western Germany, lower earnings limit, and inflation

Contribution assessment ceiling for Western Germany (Euro per year)[23]				Change of the **German Consumer Price Index**[24] to the previous year in %	Change of the **German Producer Price Index**[25] to the previous year in %
Year	**Compulsory pension insurance scheme**	**'Knappschaftliche' pension insurance**	**Lower earnings limit** (§8, Social Code IV)		
1975	17,179.41	20,860.71	2,147.40	6,03	4.66
1976	19,020.06	23,314.91	2,377.56	4,22	3.74
1977	20,860.71	25,769.11	*2,607.60	3,70	2.75
1978	22,701.36	28,223.31	2,392.80	2,72	1.17
1979	24,542.01	29,450.41	2,392.80	4,13	4.63
1980	25,769.11	31,291.06	2,392.80	5,40	7.58
1981	26,996.21	33,131.71	2,392.80	6,33	7.78
1982	28,836.86	35,585.91	2,392.80	5,24	5.99
1983	30,677.51	37,426.57	2,392.80	3,23	1.41
1984	31,904.61	39,267.22	2,392.80	2,48	2.92
1985	33,131.71	41,107.87	2,454.24	2,04	2.34
1986	34,358.81	42,334.97	2,515.56	-0,12	-2.53
1987	34,972.36	43,562.07	2,638.32	0,25	-2.35
1988	36,813.02	44,789.17	2,699.64	1,25	1.14
1989	37,426.57	46,016.27	2,760.96	2,83	3.25
1990	38,653.67	47,856.92	2,883.72	2,63	1.69
1991	39,880.77	49,084.02	2,945.04	3,73	2.38
1992	41,721.42	51,538.22	3,067.80	3,93	1.40
1993	44,175.62	54,605.97	3,251.76	3,57	0.00
1994	46,629.82	57,673.72	3,435.84	2,71	0.57
1995	47,856.92	58,900.82	3,558.60	1,63	1.71
1996	49,084.02	60,127.93	3,619.92	1,38	-1.23
1997	50,311.12	61,968.58	3,742.68	1,93	1.25
1998	51,538.22	63,195.68	3,804.00	1,00	-0.45
1999	52,151.77	63,809.23	3,865.32	0,55	-1.01
2000	52,765.32	65,036.33	3,865.32	1,42	3.07
2001	53,378.87	65,649.88	3,865.32	1,94	2.98
2002	54,000.00	66,600.00	3,900.00	1,48	-0.64
2003	61,200.00	75,000.00	3,900.00	1,04	1.73
2004	61,800.00	76,200.00	4,800.00	1,65	1.59
2005	62,400.00	76,800.00	4,800.00	1,52	4.38
2006	63,000.00	77,400.00	4,800.00	1,60	5.40
2007	63,000.00	77,400.00	4,800.00	2,26	1.33

* Ex July 1st, 1977: € 2,270.16.

23 Values from 1975 until 2001 converted from DM into Euro. Source: Deutsch Rentenversicherung Knappschaft-Bahn-See; Hauptverwaltung Bochum.

24 Consumer Price Index for Germany (1995-2007) interlinked with the cost-of-living index of all private households for West Germany (1974-1994). Source: Statistisches Bundesamt.

25 Development of prices ex 1995 are based on the development in the whole Federal Republic of Germany. Source: Statistisches Bundesamt, Fachserie 17, Reihe 2, 10/2009, p. 27.

Contribution assessment ceiling (Beitragsbemessungsgrenze):
The earnings covered by the BeH are right-censored at the contribution assessment ceiling. The contribution assessment ceiling is annually adjusted to the changes of earnings. Some employees – miners, mine-employees, sailors and railroad employees – are insured in a special pension insurance, called 'knappschaftliche' pension insurance. The contribution assessment ceiling of this pension insurance is always higher than for the compulsory pension insurance scheme (see Table A2). Since 1999, the BeH does not indicate anymore in which pension insurance a person is insured. For this reason, we only use the contribution assessment ceiling of the compulsory pension insurance scheme.

Appendix B: Impact of Inflation on the Conditional Percentiles using Quantile Regression

To observe the effect of inflation on the *conditional* percentiles of the real wage change distribution we regress real wage change Δw on the inflation rate π, the average regional real wage growth μ (as a proxy for productivity growth), and further control variables.

We make use of the Quantile Regression (Koenker and Bassett, 1978; Koenker, 2005) and model conditional percentiles of the real wage change distribution as functions of predictors:

$$Q_{\Delta w_i}(\tau \mid \mathbf{x}_{irt}) = \mathbf{x}_{irt}{}'\boldsymbol{\beta}(\tau) \text{ with } \mathbf{x}_{irt}' = (\mu_{rt} \quad \pi_t \quad \mathbf{z}_{irt}').$$

The vector $\mathbf{z}$ contains, as for the Unconditional Quantile Regression, the control variables (see Table 2). For the Quantile Regressions (QR) we use a one percent stratified sample of our data.[26]

The results (see Table B1) show that at some degree not only the highest wage increases are compressed if inflation is low (see results Chapter 4.1), but that also the highest wage increases *conditional* on the attributes of the employee and conditional on the region where the employee works are compressed if inflation is low and DNWR binds.

Table B1: Effects of inflation and productivity growth on the conditional percentiles of the real wage change distribution using Quantile Regression

	Consumer Price Index			Productivity growth		
	Coef.	Std.Err.	P>|t|	Coef.	Std.Err.	P>|t|
p10	-0.075	0.012	0.000	0.904†	0.007	0.000
p20	-0.138	0.007	0.000	0.847†	0.005	0.000
p30	-0.148	0.005	0.000	0.854†	0.004	0.000
p40	-0.152	0.004	0.000	0.865†	0.003	0.000
p50	-0.142	0.004	0.000	0.871†	0.003	0.000
p60	-0.114	0.005	0.000	0.876†	0.004	0.000
p70	-0.072	0.006	0.000	0.893†	0.005	0.000
p80	-0.019	0.009	0.036	0.906†	0.006	0.000
p90	0.002	0.017	0.909	0.919†	0.012	0.000

	Producer Price Index			Productivity growth		
	Coef.	Std.Err.	P>|t|	Coef.	Std.Err.	P>|t|
p10	0.020	0.005	0.000	0.966†	0.009	0.000
p20	-0.028	0.003	0.000	0.876†	0.004	0.000
p30	-0.060	0.002	0.000	0.849†	0.004	0.000
p40	-0.080	0.002	0.000	0.841†	0.003	0.000
p50	-0.081	0.002	0.000	0.838†	0.003	0.000
p60	-0.066	0.002	0.000	0.843†	0.004	0.000
p70	-0.044	0.002	0.000	0.866†	0.005	0.000
p80	-0.011	0.004	0.002	0.888†	0.006	0.000
p90	0.040	0.006	0.000	0.942†	0.010	0.000

Quantile Regression. Controls: region dummies, age, age squared, absolute change in inflation, current and lagged unemployment rate, dummy for the year 1984, educational class, dummy for worker with foreign nationality, occupational fields, dummy for white-collar worker. Bootstraped standard errors. 50 replications. †: coef. for productivity growth significant different from 1 on 5% level.

[26] Sample has been stratified by region, age, foreign nationality, worker class, occupational field and year.

Appendix C: Impact of Inflation on the Unconditional Percentiles using Least Squares Dummy Variable Regression

We estimate regressions with region-specific dummies of the following form by OLS: $P_{\tau_{rt}} = \alpha_\tau + \eta_\tau \pi_t + \beta_\tau \mu_{rt} + z_{rt}^{'} \rho_\tau + \varepsilon_{\tau_{rt}}$, where $P_{\tau_{rt}}$ is the τ^{th} percentile of the DFL re-weighted real wage growth distribution in region r at time t, μ_{rt} is the frictionless average real wage growth (measured using the observed regional average real wage growth rate), π_t is the inflation rate. The vector z_{rt} contains further control variables shown in Table 2.

Table C1: Effects of inflation and productivity growth on the unconditional percentiles of the real wage change distribution using Least Squares Dummy Variable Regression

	Consumer Price Index			Productivity growth		
	Coef.	R.Std. Err.	P>|t|	Coef.	R.Std. Err.	P>|t|
p10	-0.063	0.062	0.317	0.912	0.052	0.000
p20	-0.114	0.025	0.000	0.858†	0.026	0.000
p30	-0.082	0.031	0.013	0.927	0.036	0.000
p40	-0.101	0.048	0.041	0.959	0.048	0.000
p50	-0.088	0.040	0.035	0.958	0.039	0.000
p60	-0.043	0.035	0.233	0.987	0.032	0.000
p70	0.005	0.030	0.878	1.004	0.025	0.000
p80	0.047	0.032	0.144	1.024	0.030	0.000
p90	0.091	0.059	0.129	1.057	0.058	0.000

	Producer Price Index			Productivity growth		
	Coef.	R.Std. Err.	P>|t|	Coef.	R.Std. Err.	P>|t|
p10	0.007	0.019	0.722	0.945	0.044	0.000
p20	-0.032	0.013	0.021	0.889†	0.028	0.000
p30	-0.030	0.013	0.035	0.947	0.033	0.000
p40	-0.069	0.015	0.000	0.952	0.038	0.000
p50	-0.062	0.010	0.000	0.952	0.027	0.000
p60	-0.042	0.008	0.000	0.975	0.022	0.000
p70	-0.014	0.009	0.133	0.991	0.021	0.000
p80	0.017	0.013	0.181	1.018	0.030	0.000
p90	0.061	0.022	0.010	1.069	0.052	0.000

Least Squares Dummy Variable Regression. We estimate the regressions weighed by region size and relax the assumption of independence within years. Controls: regions, mean age, absolute change in inflation, current and lagged unemployment rate, dummy for the year 1984, percentage of the educational classes, percentage of workers with foreign nationality, percentage of white-collar worker, percentage of the occupational fields. †: coef. for productivity growth significant different from 1 on 5% level.

The estimated coefficients of this Least Square Dummy Variable (LSDV) regression are identical to those of the Seemingly Unrelated Regression (SUR) with small-sample adjustment and weighting by region size of Section 4.1. But the residuals differ since the LSDV regression ignores the contemporaneous correlation of the residuals.

A comparison with the results of SUR shows that all estimated coefficients of the SUR are at least as significant as the results of the LSDV regression and most coefficients of the SUR – especially those for the inflation – are even more highly significant as the coefficients of the LSDV regression.

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