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# Wage Flexibility in Turbulent Times: A Practitioner's Guide, with an Application to Poland

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**Wage Flexibility in Turbulent Times:**
**A Practitioner's Guide, with an Application to Poland**

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**Abstract**



This paper reviews several methods to measure wage flexibility, and their suitability for evaluating the extent of such flexibility during times of structural change, when wage distributions and wage curves can be particularly volatile. The paper uses nonparametric estimation to capture possible nonlinearities in the wage curve and relaxes the assumption of a stable wage distribution over time by linking the shape of the wage change distribution to macroeconomic variables. The proposed methodology is applied to Polish micro data. The estimates confirm that wages are less elastic in a high-unemployment/low-wage environment. Based on a comparison of actual and counterfactual wage distributions, the effects of nominal wage rigidities on real wages, and thus, on the labor market and the real economy, were limited until 1998, but have been quite significant thereafter.

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# I. INTRODUCTION

Wage flexibility is a key determinant of the allocative efficiency of the labor market, and thus an important aspect of overall labor market performance. If wages are flexible, they provide more accurate signals for the reallocation of labor across sectors, skill categories, or geographical regions, and facilitate the absorption of shocks or adjustment to structural changes. As a result, smaller changes in quantities—smaller increases in unemployment—may be necessary during the adjustment process.

Flexible wages can be particularly relevant to determine the length of a transition period in economies undergoing profound structural adjustments. Thus, the speed of transition from central planning to a market economy with full employment in Central and Eastern Europe hinges on how efficient labor markets react to real shocks. On the one hand, the speed and success of the adjustment so far testify to the flexibility of labor markets. On the other, in many countries, labor market performance failed to improve in recent years—unemployment remained high and participation low, even though transition to a market economy is almost complete in some places, and growth picked up. This observation raises the question of whether rigid wages play a part in some persistently weak labor market performance across Central and Eastern European Countries (CEECs)—in particular, are wages in CEECs less flexible than in advanced economies? Has wage flexibility worsened over time?

To answer these questions, I construct indicators of wage flexibility, place them in an international comparison, and trace their evolution over time. Following the literature, I consider two indicators of wage flexibility: the sensitivity of wages to unemployment and the importance of downward nominal wage rigidities.

The "wage curve" approach rests on estimating a relationship between wages and local unemployment and treats the degree of wage flexibility—the sensitivity of real wages to unemployment—as an attribute of the labor market. The question of the extent to which wages respond to changes in labor market conditions is particularly relevant in CEECs, as regional differences in unemployment are large. Because of its simple implementation and clear interpretation, the wage curve approach has been popular among policy-oriented researchers.

The starting point of the downward nominal wage rigidity approach is frictions in price-wage adjustment, and wage flexibility is considered part of the "technology" of wage setting. Whether nominal rigidities are present and how strong they are, is examined by comparing the actual distribution of wage changes to a counterfactual distribution that would be observed in the absence of nominal rigidities. If the two distributions are very different, nominal rigidities are likely to play a significant role in wage setting. The approach's insights may be valuable for the CEEC's past experience, as these countries have shifted from a high-inflation, high-wage-growth environment to moderate or low inflation and moderate wage growth. With this change in the inflation environment, nominal rigidities might have become more significant.

The paper's objectives are (i) to present a critical review of the wage curve and nominal wage rigidity literature; (ii) modify the standard empirical approaches in light of special structural or empirical features of CEECs; and (iii) illustrate the use of these modified approaches for Poland. In particular, I relax the assumption of a uniform wage elasticity with respect to local unemployment when estimating the wage curve; I also estimate the counterfactual wage change distribution in a fashion that allows the shape of the distribution to change over time, while ensuring that the estimated distribution is a valid probability measure.

A standard assumption in the wage curve literature is a uniform elasticity of wages with respect to local unemployment. However, in a high-unemployment, low-wage environment—for example, in distressed regions or following large structural shocks, both of which are relevant concerns in CEECs—wages may be less elastic for lower unemployment rates. To flexibly capture such nonlinearity and get a more accurate measure of wage flexibility, I estimate the wage curve nonparametrically. The shape of the nonparametric wage curve can then be used for a parametric specification.

Existing approaches to estimating counterfactual wage change distributions and the degree of nominal wage rigidities are not particularly well-suited for applications to CEECs—economies experiencing rapid and large structural changes and large declines in inflation rates. In particular, a common assumption in the literature is that the underlying wage change distribution is stable over time, an assumption that is unlikely to hold in a turbulent period of economic transition. I relax this assumption by linking the shape of the wage change distribution to macroeconomic variables and estimating the counterfactual distribution. In the surveyed literature, the empirical approaches do not guarantee that the estimated distributions are valid probability measures. I overcome this technical limitation—a contribution of this paper—by using an appropriate transformation, estimating the relative "bar" height of the histogram rather than its absolute scale. This makes it possible to define a measure of wage flexibility as the difference in the conditional mean wage cut between the actual case and the counterfactual case (in the absence of nominal rigidities).

I put these ideas into practice using Polish micro-level data. The results indicate that the proposed methodologies can be helpful in understanding the nature of wage rigidities in CEECs, as well as in getting a fuller picture of their development over time. Estimating a less restricted wage curve for Poland confirms that wages are less elastic in a high-unemployment, low-wage environment. Notably, In Poland until 1998, the wage curve was notably almost flat when the local unemployment rate was high (more than 14 percent), while it was fairly steep (the elasticity is -0.1) when the unemployment rate later fell. Based on the comparison of actual and counterfactual wage distributions, I find that the effects of nominal wage rigidities on real wages and, thus, on the labor market and the real economy, were small until 1998, but quite significant thereafter.

The structure of the paper is as follows. Section II reviews the wage curve literature and, with suitable modifications to the standard methodology, estimates the wage curve for Poland. Section III surveys methods of testing for nominal downward wage rigidity, develops a method appropriate for CEECs, and applies it to Polish data. Section IV concludes.

# II. The Wage Curve Approach

## A. Literature Review

The wage curve is a widely used measure of wage flexibility, capturing a negative correlation between wages and the local unemployment rate. The literature was launched by Blanchflower and Oswald (1994) who examined the role of local unemployment in wage determination in 12 countries including the United States, United Kingdom, Canada, the Republic of Korea, Germany, and some other developed European countries. Although these countries differ in size and institutional setups, the authors find an empirical regularity that holds for all of them. Their estimation results indicate that wages and the local unemployment rate are negatively correlated. Moreover, the estimated wage elasticity with respect to local unemployment is about -0.1 in all 12 countries.

This striking empirical regularity has motivated numerous subsequent papers that estimate the wage elasticity with respect to local unemployment in various countries. These papers often find a wage elasticity of about -0.1, similarly to Blanchflower and Oswald (1994). For example, Blanchflower (2001) estimates the wage curve in 23 CEECs using micro data for the years 1990–97. The estimated wage elasticity of wages with respect to the local unemployment ranges between -0.1 and -0.3. These estimates can be interpreted as evidence that wages are relatively flexible in CEECs. Others papers, such as Galuscak and Münich (2003), Huitfeldt, Kertesi and Kollo (1999), and Winter-Ebmer (1996), also estimate wage curves for CEECs using different data sets and specifications. Although the magnitude of estimates varies across papers, their results are similar to Blanchflower's.

The popularity of this approach among policy-oriented researchers is due to its easy implementation and the simple interpretation of wage elasticity as a flexibility measure. The typical econometric specification for the wage curve is a regression of log wage on the log of local unemployment and workers' individual characteristics. Although some papers use different estimation techniques to obtain more precise estimates, ordinary least squares (OLS) is generally appropriate. The interpretation of the estimates is simple: a steep wage curve indicates flexible wages because a small worsening in unemployment results in a big wage cut. This interpretation is intuitive and can be supported by economic theory.

The two main theoretical interpretations are based on bargaining models and efficiency wage models, respectively. Collective bargaining models were studied by de Menil (1971) and Carruth and Oswald (1989). In these models, the union and the firm bargain to share rents. The union's rent share is determined by its bargaining power and its outside option (alternative wage.) Assuming that bargaining power is constant over time, I can derive the wage curve, because a higher unemployment rate lowers the union's outside option value. If the value of the outside option decreases quickly as the unemployment rate increases, the wage curve is steep. When this is the case, wages are considered to be flexible.

An alternative theoretical framework for the wage curve is the efficiency wage model. In one of its most well-known renditions, developed by Shapiro and Stiglitz (1984), firms offer high wages so that the value of employment exceeds the value of unemployment, in order to prevent shirking at the job. When the unemployment rate is high and, thus, job availability is low, firms reduce wages because the penalty for shirking is heavy. Based on these principles, I can derive a wage curve that describes the negative relationship between wages and the unemployment rate so that the no-shirking condition is satisfied. If the value of the penalty for shirking is highly sensitive to the unemployment rate, the derived wage curve is steep. Again, when this is the case, wages are flexible.

**Econometric issues**

The typical econometric specification of the wage curve is a regression of log wage on the log of local unemployment rate and other individual characteristics. The equation can be estimated with aggregate data, but usually micro data are used. The wage elasticity is often estimated in the following way:

$$\ln w_{irt} = a \ln U_{rt} + bX_{irt} + d_r + f_t + e_{irt} ,$$

where $w_{irt}$ is wage for individual $i$ in the region $r$ in the period $t$, $U_{rt}$ is the local unemployment rate, $X_{irt}$ is a vector of individual characteristics such as sex, age, and education, $d_r$ is a dummy variable for the region, $f_t$ is a dummy variable for period $t$, and $e_{irt}$ is a random disturbance. I am primarily interested in the estimates of $a$.

Blanchflower and Oswald (1994) argue that a log-linear specification is a reasonable and parsimonious way to describe the wage curve. They present the estimation results for different specifications such as higher-order polynomials and dummy variables for different ranges of unemployment. They conclude that the wage curve is estimated to be a monotonically decreasing and convex function of the local unemployment regardless of the specification. They also conclude that a log-functional form is probably the best choice on account of its simplicity and precision. However, the log specification may not be the best choice in some countries. For example, wages may be less flexible at low levels, an important potential problem for countries with relatively low levels of per capita income. If this is the case, the assumption of uniform elasticity may not hold in developing or emerging countries, in particular, in CEECs. This consideration calls for a careful specification of the functional form of the relationship between wages and local unemployment rates.

Besides potential problems related to the choice of the functional form of the wage curve, estimating a wage curve raises other technical issues. In particular, although OLS is a consistent estimator for the coefficients, the estimated standard errors may be downward biased due to positive correlation across the error terms for people from the same local labor market. Wages of people in the same local labor market may be subject to common local and time-varying shocks that are entirely captured by neither the time dummy variable nor the region dummy variable. This would generate a positive correlation across the error terms for people in the same group. Card (1995) points out that such common-group effects are likely to be more of a concern than simultaneity bias or measurement error, and may lead to a significant downward bias in the estimated standard errors.

The bias can be corrected by a simple aggregation. Blanchflower and Oswald (1994) average data over all individuals in a given region at period $t$. Then the wage curve is respecified as

$$\ln w_{rt} = a \ln U_{rt} + bX_{rt} + d_r + f_t + e_{rt},$$

where $w_{rt}$ is the average wage in the region $r$ and period $t$ and $X_{rt}$ is the average of individual characteristics. Estimating the equation from the aggregated data eliminates the possible source of bias in the standard errors but leaves the coefficient estimate for the unemployment rate unchanged. However, a possible drawback is small-sample bias in the coefficients of individual characteristics.

The alternative correction method is the two-step estimation procedure proposed by Card (1995), which uses micro data to estimate the coefficients of individual characteristics but accounts for the bias from correlation across people in the same local labor market.

As a first step, a wage curve equation including time-region dummy variables is estimated from micro data:

$$\ln w_{irt} = b \ln X_{irt} + df_{rt} + e_{irt},$$

where $df_{rt}$ is a dummy variable that takes the value one if the observation is sampled from region $r$ in year $t$. Notice that in the estimated equation, the common-group effect is controlled by the dummy variable $df_{rt}$. The large variation in $X_{irt}$ helps pin down coefficients on individual characteristics precisely. In the second step, the time-region dummy is regressed on region dummies, year dummies, and the local unemployment rate:

$$df_{rt} = d_r + f_t + a \ln U_{rt} + \varepsilon_{rt},$$

where $\varepsilon_{rt}$ is a random disturbance.

**Empirical findings for CEECs**

Several papers have estimated a wage curve for CEECs. The main motivation of these papers is to see whether the wage is as flexible as wages in other EU countries and the United States and to test whether wages have become more flexible as the market reform has proceeded.

Almost all researchers find a negative wage elasticity with respect to the local unemployment rate, but the magnitude of the elasticity varies significantly. Estimates differ across econometric methods, time periods, and countries. Blanchflower (2001) estimates the wage curves of 23 transition economies, including CEECs, by OLS with micro-level data for the 1990-97 period. He finds that the wage elasticity of the local unemployment ranges between -0.1 and -0.3. This indicates that the wage elasticity in CEECs is higher than in western European countries. However, some other researchers report low elasticity estimates. For example, Huitfeldt (2001) finds a wage elasticity of between -0.01 and -0.04 in the Czech Republic for the period 1992-1998, and Galuscak and Munich (2003) estimate it to be around -0.032 between 1996 and 2001. These large differences in estimates suggest that the results are sensitive to estimation methodology; therefore, the econometric specification should be carefully chosen and the results checked for robustness.

Some papers address the question of whether wage flexibility has increased during the transition to market economy. Galuscak and Munich (2004) estimate the wage elasticity with respect to regional unemployment in the Czech Republic during 1993–2001. They allow the elasticity to vary with time. Their results show that the degree of wage flexibility did not change significantly between the early and the late transition and that the overall wage elasticity is about -0.1. In contrast, Kertesi and Köllő (1997) find that the wage elasticity in Hungary increased from -0.02 to -0.10 between 1989 and 1996. Estevão (2003) takes a different approach to assess changes in wage flexibility in Poland. He assumes that the slope of the wage curve is constant over time but the wage curve itself may shift. He finds a wage elasticity between -.06 and -0.11, and upward shifts in the wage curve in the mid-1990s, and interprets this as evidence that labor market performance in Poland has been worsening.

Although comparisons of results based on different data sets and methodologies are fraught with problems, the combined findings of previous empirical research indicate that developments in labor market flexibility may have differed across countries and time periods.

## B. Estimating the Wage Curve—An Application to Poland

In this subsection, I argue that, in contrast to the standard assumption of a uniform wage elasticity, allowing the wage elasticity to vary with the level of unemployment should be considered when the wage curve is estimated for CEECs. My preferred empirical approach is a two-stage procedure. The first step is to estimate the wage curve by nonparametric methods. The second step is to use the shape of the estimated wage curve for a suitable parametric specification. I use micro data for Poland to illustrate that this approach may yield additional insights into developments in wage flexibility in CEECs.

### Formulating the empirical approach

Most of the empirical wage curve literature assumes that the wage elasticity with respect to the local unemployment rate is constant for all wage levels after observed characteristics are controlled for. But at the lower tail end of the wage distribution, wages may be less elastic—either because of rigidities introduced by labor market institutions (such as minimum wages or social benefits), or because low-wage earnings are close to incomes from subsistence farming or shadow economy activities. In fact, there are several possible ways to take into account such nonlinearity of the wage curve. The easiest way is to include higher-order terms of the unemployment rate, for example, a quadratic and a cubic term:

$$\ln w_{irt} = a_1 \ln U_{rt} + a_2 \ln U_{rt}^2 + a_3 \ln U_{rt}^3 + bX_{irt} + d_r + f_t + e_{irt}.$$

The advantage of this approach is its simplicity, but there are practical problems. First, I do not have prior information on how many terms should be included. Second, while including higher-order terms allows me to capture a complex nonlinearity, it may also give rise to multicollinearity. Finally, the curvature of the estimated wage curve can change quite rapidly in response to a change in unemployment rate.

An alternative way is to estimate a piecewise linear wage curve. Let $D_\alpha$ be an indicator variable that takes one if the unemployment rate is lower than $\alpha$ and takes zero otherwise. The equation to be estimated is

$$\ln w_{irt} = a_1 D_\alpha \ln U_{rt} + a_2(1-D_\alpha)\ln U_{rt} + bX_{irt} + d_r + f_t + e_{irt}.$$

In this specification, I assume that the wage curve has a different slope as the unemployment rate varies. It is possible to include more than two ranges for the slope, as well as interaction terms with other covariates, such as $X_{irt}$. If the sample size is large, it is also possible to split the data into sub samples (e.g., low-unemployment and high-unemployment samples) and estimate wage curves separately. The advantage of this piece-wise linear specification is that hypothesis testing is straightforward. For example, the hypothesis of piece-wise linearity can simply be tested by comparing the estimated coefficients (e.g., $a_1$ and $a_2$ in the above specification.) However, this approach also has some practical drawbacks. Namely, I do not know how many "pieces" the curve is composed of, or where the kink points are located. Unless I know the "true" shape of the wage curve, the piecewise linear specification is difficult to implement.

The most flexible way to capture the nonlinearity of the wage curve is by using nonparametric methods. I estimate an unknown function of the wage curve

$$\ln w_{irt} = s(\ln U_{rt}) + bX_{irt} + d_r + f_t + e_{irt},$$

where $s$ is a smooth function of $U$. Notice that I assume functional forms for other covariates, such as individual characteristics ($X$) and dummy variables for region ($d_r$) and year ($f_t$), to reduce the computational burden. This specification nests all of the above approaches, such as a higher-order polynomial function and a piece-wise linear function. However, a drawback of the approach is the complex hypothesis testing, for example through nonparametric bootstrap. As I am interested in both the true shape of the wage curve and formal hypothesis testing, I propose the following two-step approach. First, I estimate the wage curve by nonparametric methods to "see" the shape of wage curve. Second, I formulate a parametric specification that reasonably approximates the nonparametrically estimated wage curve, and test my hypotheses based on the estimated parameters.

**Empirical results**

I use micro data from the Polish Labor Force Survey (LFS) for 1995-2002 period, provided by the Polish Statistical Institute (GUS)—the same data that Estevão (2003) used to estimate the wage curve in Poland.[2] To control for individual characteristics, I include age, gender,

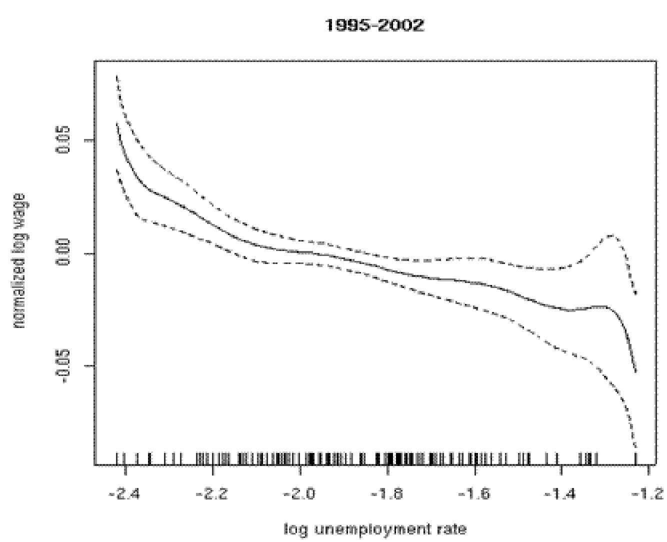
[2] The panel data are a modified version of the official Polish Labor Force Survey. To allow panel estimation of the wage curve, M. Estevão and the GUS technicians created an uniform series for individuals' region of residence for the periods before and after the Polish administrative reform of 1999. For more details on the database, see Estevão (2003).

marital status, education (7 categories), occupation (22 categories), industry (32 categories), firm ownership (private or public), dummies to indicate whether the job is temporary or whether the worker holds another job, tenure, town size (8 categories,) and firm size (16 categories.) These variables are presumably important for wage determination and could be correlated to the regional unemployment level. Wages are measured on an hourly basis and deflated by consumer price index (CPI) (= 1.00 in 1995.)[3] After omitting observations with missing values, I end up with 106,003 observations.

The wage curve is estimated by OLS and by the generalized additive model (GAM). The estimation results of both OLS and GAM are summarized in Table 3. For comparability of results, I do not apply Card's two-step method. Given my large sample size, I do not have to worry about the precision of the point estimates, but I have to take into account that their estimated standard errors are understated.

Both approaches yield reasonable estimates, in line with previous findings in the literature, for the coefficients on individual characteristics. For example, the effect of age is positive and significant, while age squared is negative and significant. Females earn significantly less than males. Married people earn significantly more than singles. Occupation, industry, town size, and firm size are jointly significant. The coefficient on the log unemployment rate is -0.064, which is very close to the estimate (-0.065) obtained by Estevão (2003), despite slight differences in variable definitions and estimation methods, and is significant.[4]

Figure 1. Wage Curve in Poland Between 1995 and 2002




Using the results of the nonparametric regression, the implied wage curve is illustrated in Figure 1 (the solid line indicates the mean of the predicted normalized log wage and the

[3] Estevão (2003) uses an indicator of technology instead of firm size.

[4] The significance of log unemployment in GAM can be tested by a Chi-squared test.

dotted lines give the 95 percent confidence envelope). Although the confidence interval for high unemployment rate levels is wide, the figure shows that the wage curve is steeper at higher wage levels and low unemployment rates. The slope of the wage curve appears to change around the point where the log unemployment rate is -2.0 (unemployment rate is about 13.5 percent.)

One possible interpretation of this finding is that the estimated wage curve is a composite of two different wage curves rather than a single nonlinear wage curve. As emphasized by Estevão (2003), a large structural change in 1998 makes this interpretation plausible. To check this possibility, I also estimate the wage curve before and after 1998 by GAM. The estimated wage curves are presented in Figure 2. Before 1998, the wage curve is almost flat when the unemployment rate is high, but it is steep when the unemployment rate is low. The wage curve also appears steeper for low unemployment rates after 1998, but the differences are considerably smaller than before 1998. However, I cannot draw strong conclusions based on these estimates, because the confidence intervals are quite wide for high unemployment rates.

To carry out formal tests, I estimate a piecewise linear wage curve. I estimate the wage curve by OLS, allowing the slope to differ before and after 1998, and for low and high unemployment rates. The estimation results are summarized in Table 4. I focus on the coefficient of the log unemployment rate here. When the unemployment rate is low, the wage curve is steep. The estimated wage elasticity is -0.125 (s.e.: 0.021) before 1998 and -.131 (s.e.: 0.041) after 1998, and the two elasticities are not significantly different.[5] These elasticities are somewhat larger than the "universal" result found in Blanchflower and Oswald (1994), which implies that for low unemployment rates, Polish wages have been slightly more flexible than in other market economies like the EU. However, for high unemployment rates, the estimated wage elasticity is merely -0.020 (s.e.: 0.022) before 1998 and -0.058 (s.e.: 0.017) after 1998. The null hypothesis that the wage elasticity is constant is rejected for both before and after 1998. Hence, I find that wages in Poland have been less elastic when the unemployment rate is high, both before and after 1998. But wages appear to become slightly more elastic for high unemployment rates after 1998.

To summarize the results of this section: I relaxed the standard assumption of a uniform wage elasticity. Specifically, I suspected that wages are less elastic when the unemployment rate is high, and tested the hypothesis using data from the Polish labor force survey. My results from a nonparametric regression (GAM) show that the wage curve is less steep when the unemployment rate is high both before and after 1998, a possible time of structural break. The results confirm that the standard assumption of a uniform wage elasticity may not be appropriate for estimating wage curves for CEECs and other emerging economies. For example, in my case the estimated elasticity is -0.0635 under the assumption of uniform wage elasticity, suggesting that wages are less flexible in Poland than in developed economies. In contrast, allowing the wage elasticity to vary, I find that, for low

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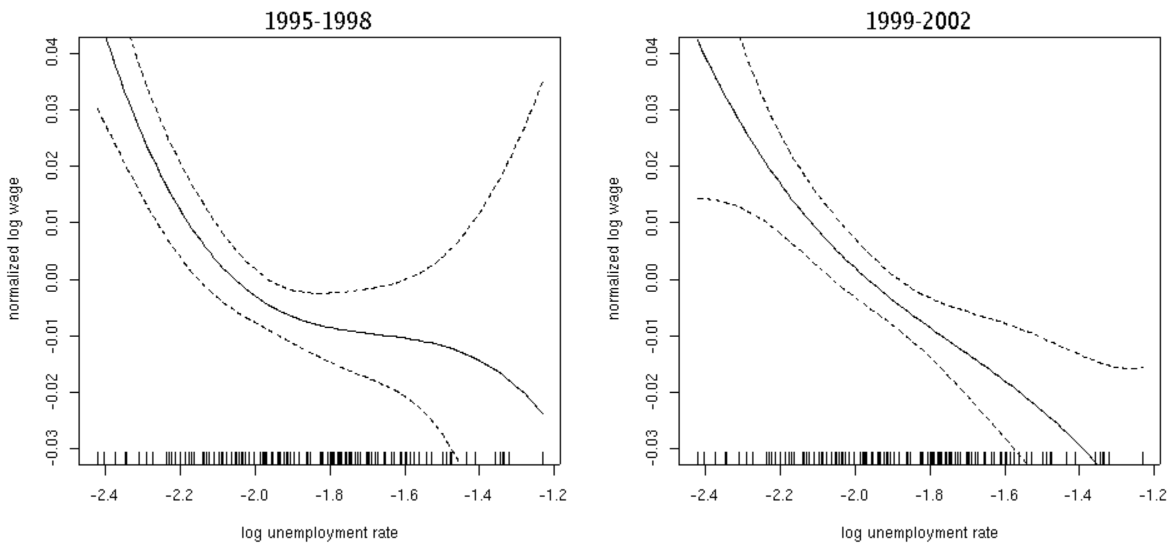
[5]The possible bias in standard error does not change this conclusion, because the bias is downward if it exists.

unemployment rates, wages in Poland are somewhat more elastic than in other developed countries. However, for high unemployment rates, wages are fairly rigid, although less so after 1998.

Figure 2. Wage Curve Before and After 1998




## III. Downward Nominal Wage Rigidity

### A. Literature Review

Another approach to studying wage flexibility is an offshoot of the nominal rigidity literature. This approach focuses on the change, instead of the level, of wages. In the classical Keynesian view, prices and wages are sticky—for example, labor market institutions tend to prevent nominal wage cuts. Nominal wage rigidity turns into real wage rigidity at low levels of inflation, and high unemployment may result. Research along these lines aims to test whether downward nominal wage rigidities exist and to check whether wages are more readily adjusted in a higher-inflation environment.

This view of downward nominal wage rigidity is supported by two stylized facts: there are few observations of wage cuts and spikes at zero in the nominal wage change distribution. Empirically, these facts can be verified by drawing a graph of the distribution of nominal wage changes (with the nominal wage change on the horizontal axis and the density on the vertical axis). Nominal rigidities provide a possible mechanism that can generate these observations. Suppose that firms want to lower nominal wages. They may find this difficult because of strong unions, harmful effects on the moral of employees, etc., and as a second best, they may keep nominal wages constant. In the absence of downward nominal wage rigidities, I would observe fewer zero nominal wage changes and more wage cuts.

The existence of downward nominal wage rigidity can be formally tested by comparing the actual wage change distribution with a counterfactual distribution, based on the assumption of full nominal flexibility. Tests rely on checking whether the spike at zero is significant or can be considered a statistical error. The method is readily extended to evaluate whether downward nominal wage rigidity influences real wage changes.

**Empirical approaches**

I review several different methods for testing downward nominal wage rigidity. The first approach is to estimate the counterfactual wage change distribution by assuming symmetry. Lebow, Stockton, and Wascher (1995) and Card and Hyslop (1997) use micro-level data and estimate individual-level nominal wage change distribution. They assume that, absent nominal rigidities, the nominal wage change distribution would be symmetric. Given this assumption, the upper half of the distribution of observed wage changes is unaffected by the rigidity as long as the median of the observed wage change is equal to or greater than zero. Then the counterfactual wage change distribution is readily recovered from the upper half of the observed wage change distribution.

Card and Hyslop (1997) specify the model in the following way. Let $f(x)$ denote the probability density function of observed wage changes in a given year. Let $\tilde{f}(x)$ be the counterfactual probability density function. Then the model is given by

$$\begin{aligned} \tilde{f}(x) &= f(x), if x \geq c \\ \tilde{f}(x) &= f(2c - x), if x < c \end{aligned},$$

where $c$ is the median of the distribution (i.e., the point of the symmetry.) The density is estimated by the standard kernel density estimates;

$$f(x) = \frac{1}{nh} \sum_{i=1}^{n} K\left(\frac{x - x_i}{h}\right)$$

where $h$ is a bandwidth and $K$ is a kernel, which can be Gaussian for example.

Two simple summary statistics for the extent of wage rigidity are proposed: a measure of the fraction of people whose wages are affected by rigidities and a measure of the net effect of rigidities on the average wage change. The former is the cumulative density of the counterfactual distribution:

$$su_t = \int_{-\infty}^{\pi_t} (\tilde{f}(x) - f(x))dx = \tilde{F}(\pi_t) - F(\pi_t)$$

where $\pi_t$ is the point of the spike in the actual distribution. The latter is measured by

$$\begin{aligned} wsu_t &= \int_{-\infty}^{\pi_t} (\tilde{f}(x) - f(x))(\pi_t - x)dx \\ &= \pi_t su_t - E(\Delta w \mid \Delta w < \pi_t; \tilde{f}) \times \tilde{F}(\pi_t) + E(\Delta w \mid \Delta w < \pi_t; f) \times F(\pi_t) \end{aligned}$$

These indicators can be easily computed once the counterfactual distribution is obtained.

The main advantage of this method is its robustness to time-varying dispersion of wage changes.[6] In addition, the estimated wage change density function is by construction a valid density function: it is positive over the distribution's support and integrates to one. This is an important practical consideration for constructing a measure of wage rigidity/flexibility such as the above. Among the other methods, only Card and Hyslop (1997)'s approach (see below) satisfies this property. The disadvantage of the approach is the restrictive assumption of symmetry.

Kahn (1997) developed a nonparametric estimation method that can identify the wage change distribution without a shape restriction. Kahn (1997) calculates the proportion of wage changes that fall into a certain range, which is equivalent to drawing a histogram. She also allows the histogram's bar to be higher when the range contains nominal zero wage change, and to be lower when the range contains negative wage change. The model is specified as follows:

$$prop_{rt} = \alpha_r + \beta_1 DNEG_{rt} + \beta_2 D1_{rt} + \beta_3 D2_{rt} + \beta_4 DN1_{rt} + \gamma D0_{rt} + \gamma_{rt},$$

where $prop_{rt}$ is the proportion of individuals whose wage change in year $t$ falls into the range between "the median wage change minus $r$ percentage points" and "the median wage change minus $r+1$ percentage points"; $D0_{rt}$ is a dummy variable that takes the value one if the zero nominal wage change falls into the $r$th percentage range; $DNEG_{rt}$ is a dummy variable that takes the value one if the $r$th percentage range includes negative nominal wage change; $D1_{rt}$ and $D2_{rt}$ are dummy variables that take one if the $r$th percentage range includes 1 and 2 percent nominal wage changes, respectively; $DN1_{rt}$ is a dummy variable that takes the value one if the $r$th percentage range includes a -1 percent nominal wage change; and $\gamma_{rt}$ and is a statistical error.

The specification assumes that, except for a random shock, the proportion of individuals in the $r$th percentage range would be the same in all years in the absence of nominal wage rigidity. However, the observed proportion of individuals in a given range may change over time if the range happens to include zero nominal wage change, negative nominal wage change, etc. These effects are captured by the dummy variables. Note that the specification does not impose any functional form for the distribution of nominal wage changes.

Kahn (1997) also assumes that the change of the bar height caused by nominal wage rigidity is constant. But it is likely that the size of the change varies with the distance between the median and zero. Consider an extreme case in which the nominal wage is perfectly downward rigid at zero. Then the size of the change is negatively correlated with the distance from the median. As the median gets closer to zero, the spike becomes larger. This does not cause a serious bias in Kahn's (1997) results because the median wage change did not change very much in her sample period. However, the bias may be important if the median changes significantly over time—which is actually the case in many CEECs.

[6] This contrasts with the nonparametric method by Kahn (1997), which we will see below.

The most attractive feature of this approach is the lack of shape restrictions. But an important underlying assumption is no change in the (otherwise unrestricted) shape of the underlying distribution. In fact, the shape of the counterfactual distribution is identified from the time variations of the median wage change, assuming that the shape is stable over time. This assumption will likely be violated if inflation and economic growth change significantly over the sample period, as wage changes tend to be correlated with these macroeconomic variables.

Nickell and Quintini (2003) develop an econometric method that is robust to both the asymmetry of the wage change distribution and the time-varying wage dispersion. They examine the proportion of individuals who experienced wage cuts in relation to the median wage change, wage change dispersion, and inflation. They focus on real wages instead of nominal wages to examine how inflation mitigates wage rigidity in real terms.

The model is specified in the following way:

$$prop^{i}_{t,\Delta w\leq\alpha} = \beta_0 + \beta_1 \Delta w_t^{i,m} + \beta_2 (\Delta w_t^{i,m})^2 + \beta_3 \Delta p_t + \beta_4 d^{75-35} \Delta w_t^i + \beta_5 d^i + \sum_{j=6}^{J} \beta_j d_j \Delta p_t + \varepsilon_{it},$$

where $prop^{i}_{t,\Delta w\leq\alpha}$ is the proportion of individuals who experienced the real wage cut $\alpha$, $\Delta w_t^{i,m}$ is the median real wage change in the region $i$ in year $t$, $\Delta p_t$ is inflation, $d^{75-35}\Delta w_t^i$ is the percentage point difference between the real wage change for the 75th percentile and the 35th percentile, $d^i$ is the region dummy, $d_j \Delta p_t$ is a dummy variable that takes the value one if the inflation in year $t$ falls in the $j$ th region such as between 3 percent and 5 percent, and $\varepsilon$ is the random error. Notice that this method is related to the one proposed by Kahn (1997) in the sense that the former is the regression of a cumulative distribution function and the latter is the regression of a density function. The departure from Kahn's method is to include the variables of change in the median wage and a measure of wage dispersion.

The method proposed by Nickell and Quintini (2003) has the merit of robustness to asymmetry and to time-varying dispersion. Of course, the linear-quadratic form for the cumulative density function might be misspecified and thus the estimates might be biased. However, the counterfactual wage change distribution could be well approximated by higher-order polynomials even if it has a complex shape, such as the multimodal distribution.

Altonji and Devereux (2000) control individual characteristics and test downward nominal wage rigidity. They define the "notional wage" as the wage the firm would pay in the absence of downward nominal wage rigidity. The notional wage is specified as a linear function of individual characteristics. If the notional wage change cut is less than a critical value $-\alpha$, the actual nominal wage change is zero. The model allows nominal wage cuts to occur when the notional wage change is sufficiently negative. The notional wage $w_{it}^*$ is given by

$$w_{it}^* = x_{it}\beta + \varepsilon_{it},$$

where $x_{it}$ is a vector of individual characteristics and other explanatory variables, $\beta$ is a parameter vector, and $\varepsilon_{it}$ is a normally distributed error term. If the notional wage change is a nominal wage cut less than $-\alpha$, then firms set the actual nominal wage change to zero. When the notional change is less than $-\alpha$, the actual wage change is the notional change plus $\lambda$, which means the wage cut is lightened by $\lambda$. The model specifies the relationship between the notional change and the actual change as follows:

$$\begin{array}{rcll} w_{it}^0 - w_{it-1}^0 & = & x_{it}\beta - w_{it-1}^0 + \varepsilon_{it} & if \quad 0 \le x_{it}\beta - w_{it-1}^0 + \varepsilon_{it} \\ w_{it}^0 - w_{it-1}^0 & = & 0 & if \quad -\alpha \le x_{it}\beta - w_{it-1}^0 + \varepsilon_{it} \le 0, \\ w_{it}^0 - w_{it-1}^0 & = & \lambda + x_{it}\beta - w_{it-1}^0 + \varepsilon_{it} & if \quad x_{it}\beta - w_{it-1}^0 + \varepsilon_{it} \le -\alpha \end{array}$$

where $w_{it}^0$ is the nominal wage of individual $i$ at period $t$. Finally, the authors account for measurement error in observed wages:

$$w_{it} = w_{it}^0 + u_{it},$$

where $w_{it}$ is the observed wage. The parameters are estimated by maximum likelihood.

This structural approach gives a clear interpretation of the estimates. Altonji and Devereux (2000) call $\alpha$ the measurement of wage rigidity. In the special case where $\alpha$ is infinity, we never observe a wage cut. In the other extreme case where $\alpha = \lambda = 0$, wages are fully flexible and the notional wage change and the actual wage change coincide. In addition, the model is robust to compositional changes such as age effects. The notional wage change may vary across people. For example, it is widely observed that the average wage growth rate is higher for the young than for the old. It then follows that the notional wage change distribution varies with demographic changes.

However, the wage setting specified in this model is relatively restrictive. Namely, it assumes that for nominal wage increases, the notional wage change distribution coincides with the counterfactual wage distribution. Furthermore, it assumes that the actual wage change distribution has zero density between zero and the critical value.

### B. Estimating the Underlying Wage Change Distribution—An Application to Poland

All estimation methods presented above more or less assume a stable distribution to identify the counterfactual wage change distribution. Although I admit that stability of the distribution is necessary for identification, the existing methods can be too restrictive because CEECs have been experiencing large structural changes. Specifically, the main problems are shifts in the median of the distribution and changes in its dispersion. For example, if structural change is rapid and inflation high, the median wage growth will be high and the wage dispersion large, with losers absorbing large real wage cuts and winners getting large real wage increases. When this is the case, because of high inflation, nominal rigidities are not really binding (as, for example, in the case of Poland in 1994). With a more advanced transition, the situation consolidates: structural change becomes smaller, reflected in a smaller wage dispersion, and inflation and nominal wage growth is lower (as, for example, in the case of Poland in 2002).

Another problem with the existing methods is that the predicted value does not generally satisfy the conditions for a probability measure: the predicted bar height of the histogram is not necessarily positive and the sum of the predictions is not necessarily one. This should not be a problem if the objective is to test for the existence of nominal wage rigidity, like in Kahn (1997). However, my objective goes beyond this. As is shown in Figure 4 and Table 6, many Polish workers are apparently protected by the "barrier" of the zero nominal wage rigidity in 2002. An interesting policy question is how much of a wage cut workers could have experienced if there were no nominal rigidities—presumably also leading to higher levels of employment. To answer this sort of question, I need to construct a valid counterfactual wage change distribution.

I propose a novel way to control for the rapid structural changes while also generating a valid counterfactual wage change distribution. First, I present my econometric specification, and then discuss its merits for an application to CEECs.

Similarly to Kahn (1997) and Nickell and Quintini (2003), my approach is based on estimating bar heights from the actual wage change distribution. I capture structural changes by including a measure of wage dispersion, median wage change, and the change rate of terms of trade among the regressors. Let $DIFF_{rt}$ be the difference in the wage change rate between the median and the $r$ th bar (I have $R$ bars in total) in period $t$. Let $DISP_{rt}$ be the difference between the 90th percentile of the wage change rate and the 60th percentile of the wage change rate. This can be interpreted as a measure of wage dispersion. Notice that this measure is not affected by possible nominal wage rigidity because at the 60th percentile the wage change rate is always positive in my sample. I also include the change rate of terms of trade $\Delta TRD_t$ to capture a macroeconomic environment that may affect the wage change distribution. The econometric specification is given by:

$$h_{rt} = \frac{\exp(x_{rt}\beta)}{\sum_{i=1}^{R}\exp(x_{it}\beta)} + \varepsilon_{rt}$$

$$\begin{aligned} x_{rt}\beta = {} & \beta_1 DIFF_{rt} + \beta_2 DIFF_{rt}^2 + \beta_3 DIFF_{rt}^3 + \beta_4 DIFF_{rt} \cdot DISP_t + \beta_5 DIFF_{rt} \cdot DISP_t^2 + \\ & \beta_6 DIFF_{rt}^2 \cdot DISP_r + \beta_7 DIFF_{rt} \cdot \Delta TRD_t + \beta_8 D0_{rt} + \beta_9 D0_{rt} \cdot DIFF_t + \\ & \beta_{10} D0_{rt} \cdot DISP_t + \beta_{11} DN_{rt} + \beta_{12} DN_{rt} \cdot DIFF_t + \beta_{13} DN_{rt} \cdot DISP_t, \end{aligned}$$

where $h_{rt}$ is the height of $r$ th bar at period $t$, $D0_{rt}$ is a dummy variable that takes the value one if the range of the bar includes nominal zero wage change, $DN_{rt}$ is a dummy variable that takes the value one if the range of the bar includes only the nominal negative region, and $\varepsilon_{rt}$ is a normally distributed disturbance term with mean zero and variance $\sigma_{\varepsilon}^2$.

The proposed specification restricts the predicted value of each bar to be positive and the sum of the estimates bar heights to be one. Notice that this specification cannot include a variable that is common to all bars. One obvious example of this is an intercept. If I include such a variable, it would multiply the absolute height of a bar. Because all bars are multiplied by it, this would not affect the relative height. For this reason, I cannot include terms such as $DISP_t$ or $\Delta TRD_t$ without interacting with $DIFF_r(m,r)$.

The effect of structural change on the nominal wage change distribution is flexibly captured by including higher-order polynomials. Specifically, I use the third-order polynomial of the difference from the median and the measure of dispersion, including interaction terms. I consider the third-order polynomial as parsimonious and flexible enough to capture the shape of the underlying distribution for the following reasons. As Kahn (1997) and Nickell and Quintini (2003) pointed out, the underlying distribution is plausibly asymmetric. Second-order polynomials could not capture this—at least a third-order polynomial is necessary. While higher-order polynomials give more flexibility, they may also lead to multicollinearity, resulting in imprecise estimates. In addition, a small change of the explanatory variable is converted into a huge change of the bar height. This means that a measurement error or a statistical error may be propagated when I construct a counterfactual distribution. Based on these arguments, I prefer using a third-order polynomial.

My specification allows the change of the bar height at nominal zero and nominal negative to vary with the distance from the median. Kahn (1997) does not allow this variation, while Nickell and Quintini (2003) estimate it nonparametrically, which requires many observations. As one can easily see from the histogram for Poland, the change of the bar height apparently varies with the distance from the median. At the same time, my sample covers seven years only, which is insufficient to apply Nickell and Quintini's (2003) method. My specification stands between these two papers and reasonably approximates the underlying relationship.

The exact specification of the estimation is as follows. I constructed 50 bars for each year, with the 26th bar covering the median of the wage distribution of each year. Some observations not be covered by this histogram are simply ignored rather than aggregated in the 1st or 50th bar. The bandwidth of a bar is set to 0.02 and all bars have strictly positive heights for all years. If I increase the number of bars or the bandwidth, I would have a bar with zero height. The parameters are estimated by maximum likelihood and the estimates are summarized in Table 5. First, my model captures the asymmetry of the underlying distribution, indicated by the positive and significant coefficient of $DIFF^3$. Second, the estimates indicate nominal wage rigidity at zero, and the effect becomes stronger when the nominal zero is closer to the median and when wages are more dispersed. Third, the bar height is reduced when it is in the nominal negative region, which can be interpreted as further evidence of downward nominal wage rigidity. The effect is getting weaker when the bar gets far from the nominal zero (or median) or when wages are more dispersed.

Using my estimates, the predicted distribution and estimated underlying distribution are presented in Figure 5 through Figure 8. The predicted distribution is based on the fitted values, i.e., it is constructed by using all the regressors in the equation. Because these graphs are obtained by removing noise, I can interpret them as a "smooth" version of the histogram of the actual wage change distribution. In contrast, the underlying distribution is constructed by assuming that there is no nominal wage rigidity – that is, I set the dummy variables for nominal zero and nominal negative as zero. Although the predicted distribution seems a little "oversmoothed" from the observed distribution, important properties such as the spike at zero and asymmetry are captured. The graphs of the underlying distribution are also asymmetric, although less so than the predicted distribution—for example, in 1995, the underlying distribution has a thicker right than left tail.

Table 1. The Conditional Mean Real Wage Cut, 1995-2002
(Given any real wage cut)

| | 1995 | 1996 | 1997 | 1998 | 1999 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| Observed | -0.21 | -0.16 | -0.16 | -0.13 | -0.10 | -0.10 | -0.06 |
| Counter Factual | -0.21 | -0.18 | -0.18 | -0.15 | -0.14 | -0.15 | -0.14 |
| | 0.00 | 0.02 | 0.02 | 0.02 | 0.04 | 0.05 | 0.08 |
| Unemployment Rate | 0.15 | 0.14 | 0.13 | 0.11 | 0.13 | 0.19 | 0.21 |

I define my measure of wage flexibility as the difference in the mean wage cut between the observed distribution and the counterfactual distribution. The measure *wageflex* is formally defined as:

$$wageflex = \sum_{r \in NEG} \Delta w_r (p_r - \hat{p}_r),$$

where $p_r = h_r / \sum_{i \in NEG} h_i$ is the conditional probability that observations fall into $r$ th bar given any wage cu. When wages are flexible, this measure is close to zero because the estimated wage change distribution is not different from the observed wage change distribution. However, when wages are rigid, the measure is large because workers would have experienced a larger wage cut than actually observed.

Table 2. The Conditional Median Real Wage Cut, 1995-2002
(Given any real wage cut)

| | 1995 | 1996 | 1997 | 1998 | 1999 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| Observed | -0.0029 | -0.0023 | -0.0021 | -0.0016 | -0.0012 | -0.0013 | -0.0009 |
| Counter Factual | -0.0035 | -0.0031 | -0.0034 | -0.0028 | -0.0026 | -0.0032 | -0.0032 |
| *wageflex* | 0.0006 | 0.0008 | 0.0013 | 0.0012 | 0.0014 | 0.0019 | 0.0023 |
| Unemployment Rate | 0.15 | 0.14 | 0.13 | 0.11 | 0.13 | 0.19 | 0.21 |

It may be useful to construct the median version of the wage flexibility measure, because the conditional wage distribution is left skewed due to truncation. The measure $wageflex_{MED}$ is defined as:

$$wageflex_{MED} = MED(w_r \mid p_r, r \in NEG) - MED(w_r \mid \hat{p}_r, r \in NEG),$$

where $MED(w_r \mid p_r)$ is the operator for the median of $w_r$ when the probability mass function is given by $p_r$.

From the histogram of the observed wage distribution, I infer that downward nominal wage rigidity did not affect real wage flexibility in the middle of 1990s, while it did affect it early in 2000s. My measures of wage flexibility seem consistent with this intuition. Table 1 and Table 2 summarize both the mean and the median versions of the measure of wage flexibility in each year. Let us examine the evolution of the flexibility measure based on conditional mean wage cuts. In 1995, it is zero, which implies that nominal wage rigidity did not distort the labor market at all. In that year, both inflation and the median wage growth rate were high, and nominal wage rigidities were not really binding. As economic transition progressed, the situation "consolidated": structural changes became smaller, and inflation and wage growth lower. Therefore, nominal rigidities gradually became more binding, as reflected by the increase in the conditional wage cut. The picture is similar if I examine the flexibility measure based on conditional median wage cuts—its value is smallest in 1995, and then it gradually increases and reaches its highest level in the last year of the sample.

The results presented in this section are consistent with the ones obtained by estimating the wage. From 1995 to 1998, the national average unemployment rate was 11-15 percent, implying that the average worker was located in the steep part of the wage curve. Although the unemployment rate varied across regions, and wages in high-unemployment regions may have been rigid, on average wages were fairly flexible—recall that I estimated that when the unemployment rate is less than 13.5 percent the wage elasticity is -0.125. However, from 1999 to 2002, the national average unemployment rate was 12.8-20.6 percent, implying that the average Polish worker was on the less steep part of the wage curve, where wages are less elastic with respect to unemployment (elasticity estimated at -0.058).

My interpretation is that before 1998, although nominal wages were quite rigid in high-unemployment regions (possibly due to labor market institutions), high average wage growth and high inflation shielded the Polish labor market from the adverse consequences of downward nominal rigidities. Real wages became the variable that provided the adjustment in the labor market. As reforms proceeded, the sources of nominal wage rigidities started to disappear at the local level, and wages became more flexible after 1998. Indeed, the evidence is that wages became more elastic at all unemployment levels. However, low average wage growth, low inflation, and downward nominal wage rigidity, hindered real wage flexibility, leading to an adjustment primarily through quantities (employment) rather than prices in the labor market. In Poland, downward nominal wage rigidity in an environment of low inflation prevented the type of real wage adjustment that did the trick in the labor market before 1998 and thus led to high unemployment.

## IV. CONCLUSION

The paper reviewed several methods to measure wage flexibility and developed new approaches that are particularly suitable for CEECs. In particular, I applied nonparametric techniques to capture a possibly important nonlinearity in the wage curve. In addition, I estimated the underlying wage change distribution that is suitable for gauging the extent of downward nominal wage rigidity in a changing macroeconomic environment.

To illustrate the use of these techniques for a CEEC, I estimated the wage curve and the underlying wage change distribution for Poland. The estimated wage curve confirms the presence of the suspected nonlinearity—the results suggest that wages are less flexible when the local unemployment rate is high. Results from estimating the underlying wage change distribution suggest that nominal wage rigidities did not translate into real wage rigidity in the high-inflation pre-1998 period but started to matter as inflation declined. For example, in 2002, while the actual average wage cut was 6 percent, I estimate that the average wage cut would have been 14 percent in the absence of nominal wage rigidities (full wage flexibility). This development went hand in hand with a significant increase in aggregate unemployment.

My interpretation is that before 1998 nominal wage rigidities mattered little; the wages of the average Polish worker—situated on the steep section of the wage curve—were sensitive to local unemployment. After 1998, partly reflecting downward nominal wage rigidities caused by low inflation and low economic growth, real wages became less flexible and unemployment increased. Although—possibly due to economic reforms—the wage curve became steeper at all local unemployment levels; the average Polish worker was on the flat section of the wage curve, with fairly rigid wages due to higher unemployment.

A key conclusion from this analysis is that, although a low or moderate inflation rate is usually preferred from the viewpoint of the macroeconomy as a whole, reduced inflation might have had negative side effects on the labor market in Poland. Specifically, it might have hindered the adjustment in the (aggregate) Polish labor market after 1998, and thus might have contributed to a higher unemployment rate.

Figure 3. Observed Wage Change Rate Distribution, 1995-98

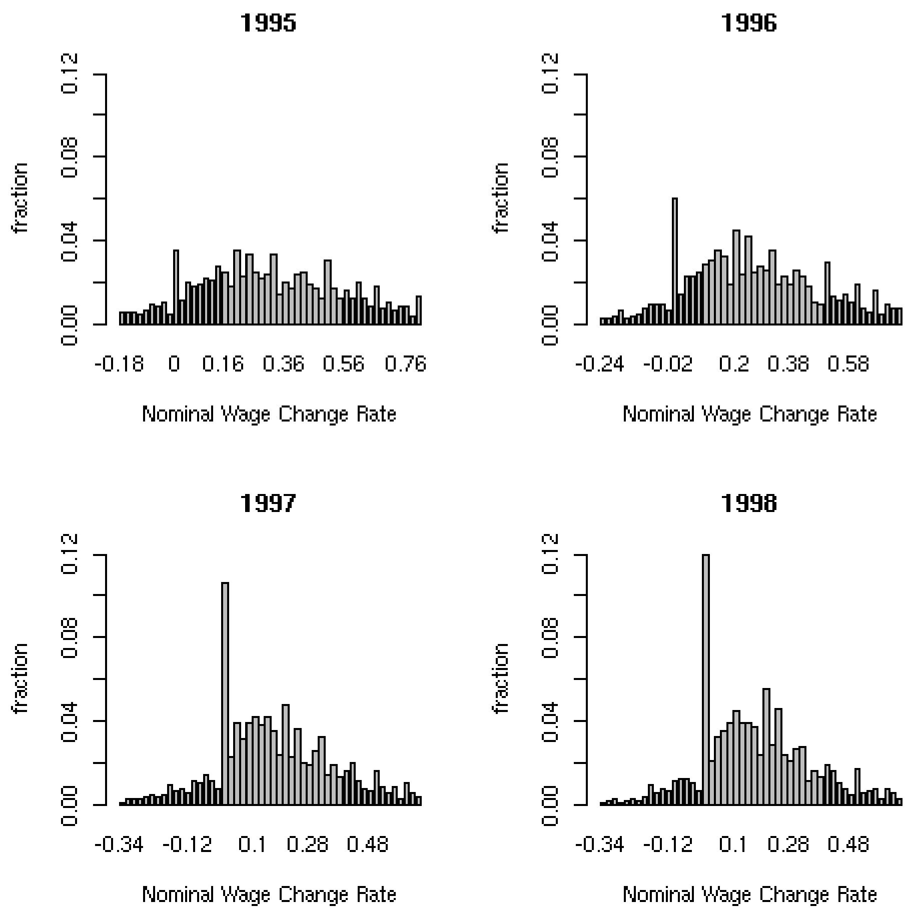


Figure 4. Observed Wage Change Rate Distribution, 1999-2002

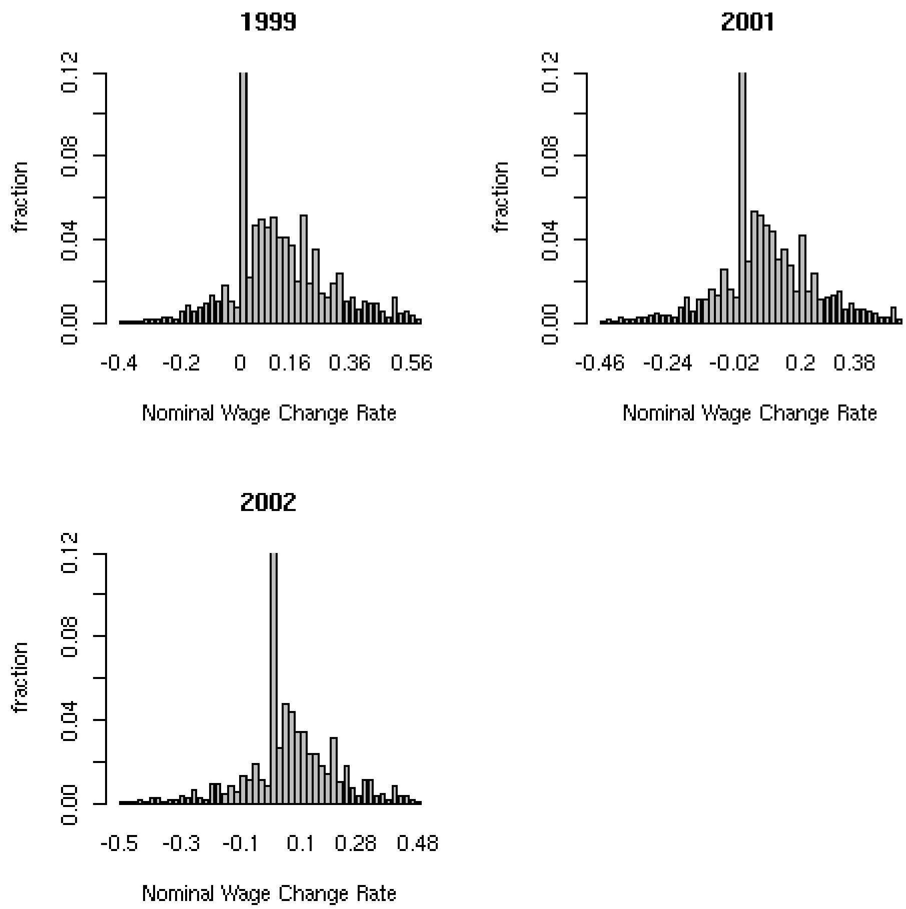


Figure 5. Fitted Wage Change Rate Distribution, 1995-98

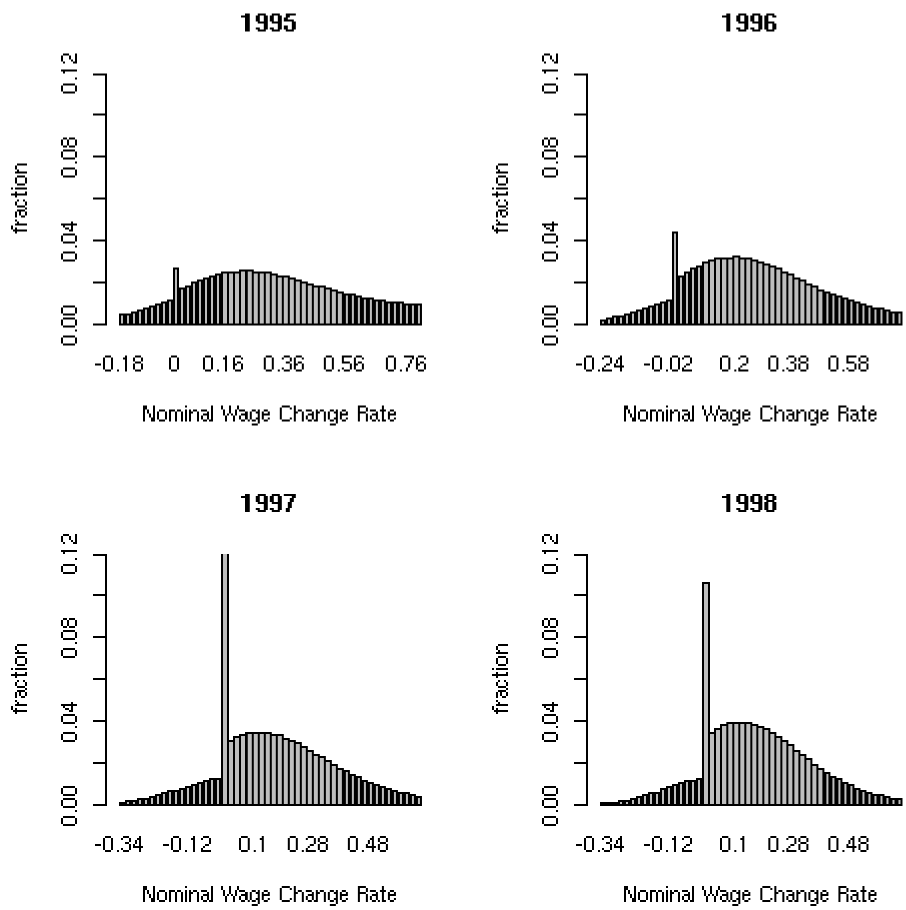


Figure 6. Fitted Wage Change Rate Distribution, 1999-2002

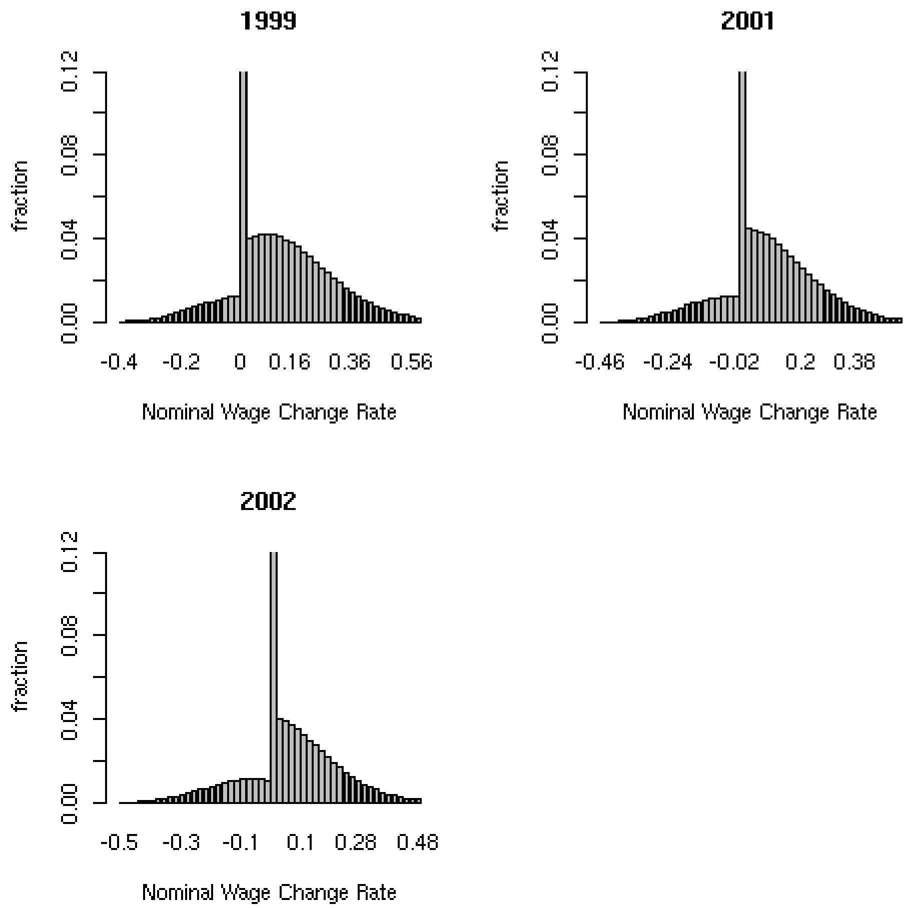


Figure 7. Underlying Wage Change Distribution, 1995-98

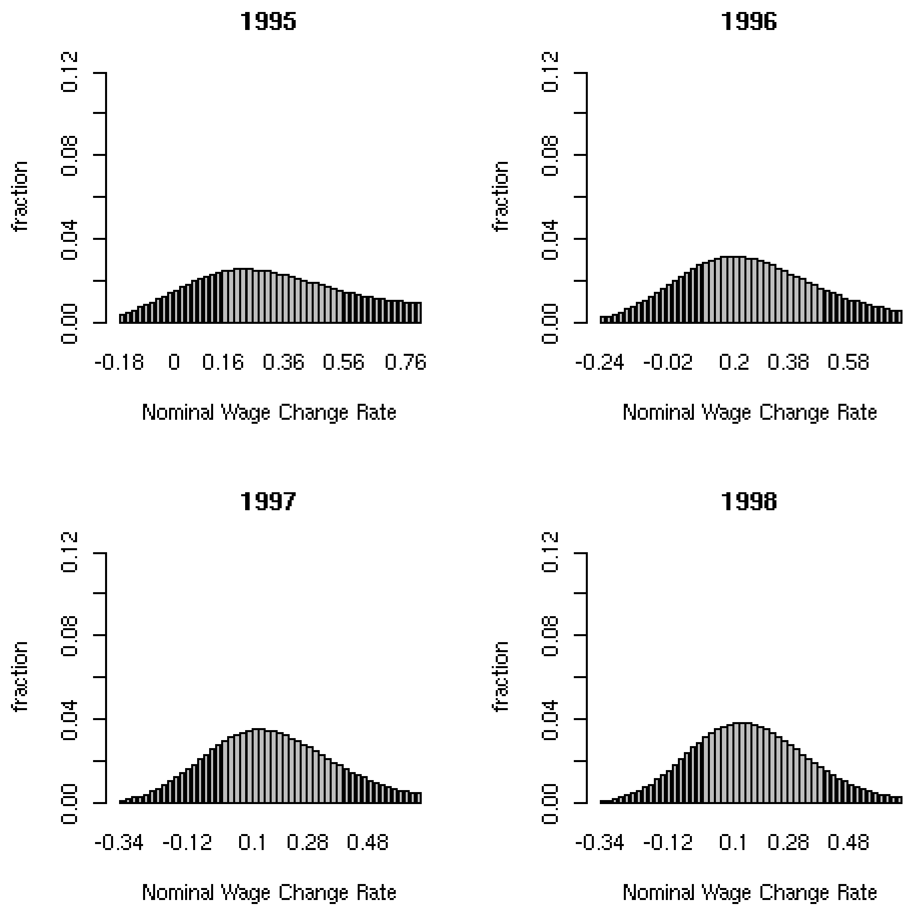


Figure 8. Underlying Wage Change Distribution, 1999-2002

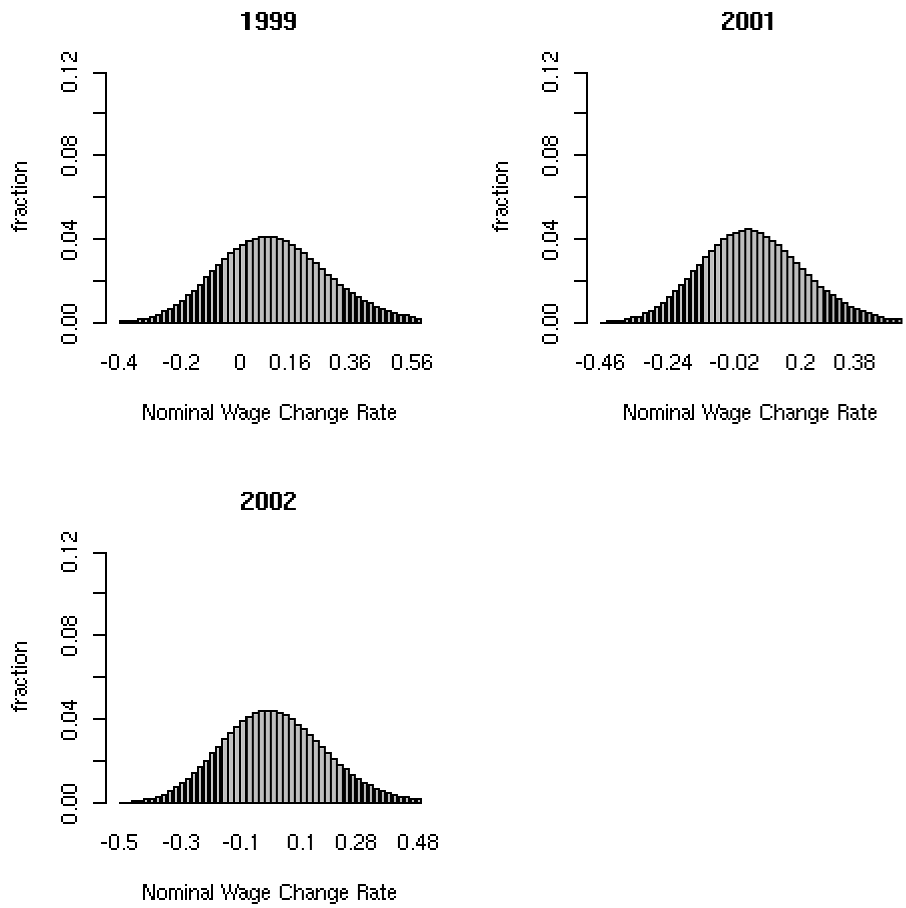


Table 3. Estimation of Wage Curve

| | OLS | | GAM | |
|---|---|---|---|---|
| | Estimate | Std. Error | Estimate | Std. Error |
| Intercept | 2.3988 | 0.0431 | 2.5194 | 0.0371 |
| $\ln U$ | -0.0635 | 0.0132 | | |
| Female | -0.1390 | 0.0026 | -0.1390 | 0.0026 |
| Married | 0.0679 | 0.0032 | 0.0679 | 0.0032 |
| Age | 0.0136 | 0.0008 | 0.0137 | 0.0008 |
| $\text{Age}^2/100$ | -0.0134 | 0.0010 | -0.0134 | 0.0010 |
| Temp. Job | -0.1676 | 0.0052 | -0.1676 | 0.0052 |
| Tenure | 0.0020 | 0.0001 | 0.0020 | 0.0001 |
| Additional Job | -0.0022 | 0.0035 | -0.0022 | 0.0035 |
| No of Obs. | 106003 | | 106003 | |
| Adj. $R^2$ | 0.594 | | 0.594 | |

Approximate significance of smooth term

| | Equiv. DF | $X^2$ |
|---|---|---|
| s(lnU) | 9 | 42.442 |

Note: Dummy variables for year, region, occupation, industry, firm size, town size, and education are omitted from the table.

Table 4. Wage Curve by Unemployment Level

| | OLS | | GAM | |
|---|---|---|---|---|
| | Estimate | Std. Error | Estimate | Std. Error |
| Intercept | 2.2594 | 0.0559 | 2.5222 | 0.0371 |
| $D_{late}D_{high} \ln U$ | -0.0578 | 0.0168 | | |
| $D_{late}D_{low} \ln U$ | -0.1311 | 0.0412 | | |
| $D_{early}D_{high} \ln U$ | -0.0203 | 0.0221 | | |
| $D_{early}D_{low} \ln U$ | -0.1253 | 0.0208 | | |
| Female | -0.1390 | 0.0026 | -0.1390 | 0.0026 |
| Married | 0.0679 | 0.0032 | 0.0679 | 0.0032 |
| Age | 0.0136 | 0.0008 | 0.0136 | 0.0008 |
| $\text{Age}^2/100$ | -0.0134 | 0.0010 | -0.0134 | 0.0010 |
| Temp. Job | -0.1675 | 0.0052 | -0.1676 | 0.0052 |
| Tenure | 0.0020 | 0.0001 | 0.0020 | 0.0001 |
| Additional Job | -0.0021 | 0.0035 | -0.0022 | 0.0035 |
| No. of Obs. | 106003 | | 106003 | |
| Adj. $R^2$ | 0.5942 | | 0.5942 | |

Approximate significance of smooth terms

| | Estim. DF | $X^2$ |
|---|---|---|
| $D_{early}s(\ln U)$ | 3 | 35.836 |
| $D_{late}s(\ln U)$ | 3 | 16.761 |

Notes: $D_{early} = I(year \leq 1998), D_{late} = I(year > 1998), D_{low} = I(\ln U < -2)$, and $D_{high} = I(\ln U > -2)$ where $\ln U = -2$ means unemployment rate $U$ is approximately 13.5 percent. Dummy variables for year, region, occupation, industry, firm size, town size, and education are omitted from the table.

Table 5. Estimation of Underlying Distribution of Wage Change

| | Estimate | Std. Error |
|---|---:|---:|
| $DIFF$ | 0.5128 | 0.5183 |
| $DIFF^2$ | -0.3093 | 0.0489 |
| $DIFF^3$ | 0.0082 | 0.0034 |
| $DIFF \cdot DISP$ | -0.3348 | 0.2826 |
| $DIFF \cdot DISP^2$ | 0.0419 | 0.0371 |
| $DIFF^2 \cdot DISP$ | 0.0552 | 0.0109 |
| $DIFF \cdot \Delta TRADE$ | 0.2828 | 0.2724 |
| $D0$ | 0.4980 | 0.4187 |
| $D0 \cdot DIFF$ | 0.9994 | 0.0986 |
| $D0 \cdot DISP$ | 0.7034 | 0.1610 |
| $DN$ | -2.0057 | 0.6229 |
| $DN \cdot DIFF$ | -0.1843 | 0.1733 |
| $D0 \cdot DISP$ | 0.2489 | 0.2504 |
| $\sigma_\varepsilon^2$ | 0.0063 | 0.0002 |
| No of obs | 350 | |
| Log likelihood | -1272.451 | |

Notes: Parameters are estimated by maximum likelihood.
Error terms are assumed to be normally distributed with zero mean and variance $\sigma_\varepsilon^2$. The bandwidth of the histogram is set to 0.02.
The number of bars in each year is 50.

Table 6. Observed and Counterfactual Wage Cut, 1995-2002

Observed Nominal Wage Cut

| | 1995 | 1996 | 1997 | 1998 | 1999 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| = .00 | 0.04 | 0.06 | 0.11 | 0.12 | 0.20 | 0.26 | 0.42 |
| <.00 | 0.12 | 0.09 | 0.12 | 0.11 | 0.12 | 0.17 | 0.14 |
| <.05 | 0.10 | 0.07 | 0.10 | 0.09 | 0.10 | 0.15 | 0.12 |
| <.10 | 0.08 | 0.04 | 0.07 | 0.06 | 0.06 | 0.09 | 0.08 |

Counterfactual Nominal Wage Cut

| | 1995 | 1996 | 1997 | 1998 | 1999 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| = .00 | 0.02 | 0.02 | 0.03 | 0.03 | 0.04 | 0.04 | 0.04 |
| <.00 | 0.13 | 0.13 | 0.21 | 0.21 | 0.27 | 0.39 | 0.47 |
| <.05 | 0.11 | 0.09 | 0.16 | 0.15 | 0.20 | 0.31 | 0.38 |
| <.10 | 0.08 | 0.05 | 0.10 | 0.09 | 0.12 | 0.20 | 0.26 |

Observed Real Wage Cut

| | 1995 | 1996 | 1997 | 1998 | 1999 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| <.00 | 0.45 | 0.38 | 0.44 | 0.40 | 0.44 | 0.52 | 0.56 |
| <.05 | 0.39 | 0.29 | 0.36 | 0.28 | 0.34 | 0.17 | 0.12 |
| <.10 | 0.32 | 0.23 | 0.29 | 0.23 | 0.11 | 0.15 | 0.09 |

Counterfactual Real Wage Cut

| | 1995 | 1996 | 1997 | 1998 | 1999 | 2001 | 2002 |
|---|---|---|---|---|---|---|---|
| <.00 | 0.45 | 0.40 | 0.45 | 0.42 | 0.43 | 0.53 | 0.51 |
| <.05 | 0.39 | 0.31 | 0.38 | 0.31 | 0.35 | 0.39 | 0.38 |
| <.10 | 0.32 | 0.25 | 0.31 | 0.24 | 0.24 | 0.31 | 0.30 |

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