Patterns of Nominal and Real Wage Rigidity

Louis N. Christofides*
University of Cyprus and University of Guelph

Paris Nearchou
University of Cyprus

September 15, 2007

Abstract

We study the distortions that downward nominal and real wage rigidity would induce to a flexible form of a notional, rigidity-free, distribution of wage change using the histogram-location approach. We examine alternative methods of generating the histograms that support the econometric search for rigidity distortions and implement our approach to inflation subperiods that should be characterised by different patterns of nominal and real rigidities. We establish the general applicability of the approach to these subperiods and find results consistent with expectations.

JEL Classification: J52, J31

Keywords: Real, nominal wage rigidities.

*Correspondence should be addressed to: L. N. Christofides, Department of Economics, University of Cyprus, Kallipoleos 75, P.O.Box 20537, 1678 Nicosia, CYPRUS. Phone: 357 22 892448 Fax: 357 22 892432. Email: louis.christofides@ucy.ac.cy. Christofides is a University Professor Emeritus at the University of Guelph, a Research Associate at CLLRNet and CESifo and a Research Fellow at IZA. We thank M. Legault, Human Resources Development Canada, for the data and the Social Sciences and Humanities Research Council for financial support. Earlier versions of this work were presented by Nearchou at the September 2006 EALE conference in Prague and the 9th IZA European Summer School in Labor Economics in April 2006. This paper was produced for the "Wage Bargaining, Employment, and Monetary and Economic Policies" conference, organised by the Banque de France on October 9,10 in Paris.

1 Introduction

In Keynesian models, the notion of downward nominal wage rigidity (DNWR) plays an important role in 'rationalising' the failure of the labour market to clear and the existence of unemployment. In these models, employment is determined along the labour demand curve (the 'short' side of the market) and, since increases in employment require movements along this demand curve, the real wage behaves counter-cyclically. Early attempts (Dunlop (1938) and Tarshis (1939)), but also more recent papers (Solon et al (1994) and Abraham and Haltiwanger (1995), examine nominal wage rigidity indirectly by looking at the cyclical properties of the real wage rate.[1]

McLaughlin's (1994) paper shifted attention to wage growth distributions (WGD) for individuals in panel data, thus giving rise to a more inductive approach to this issue: What do data on the earnings of individuals over time imply about wage rigidity? The papers by, *inter alia*, Lebow *et al* (1995), Fortin (1996), Kahn (1997), Card and Hyslop (1997), Crawford and Harrison (1998), Smith (2000), Altonji and Devereux (2000), Christofides and Stengos (2001, 2002, 2003), Christofides and Leung (2003), Christofides and Li (2005), Dickens and Groshen (2004), and Holden and Wulfsberg (2007) all follow this broad approach. Some of these papers deal not only with DNWR but, also, with aspects of real wage rigidity.

The extent to which DNWR and downward real wage rigidity (DRWR) coexist and interact are points that are worth investigating further.[2] Papers which address both types of rigidity

[1]In the context of more contemporary models, where productivity shocks shift the labour demand curve, the real wage rate may be procyclical.

[2]As an extreme example, in the case of firm and uniform inflation expectations, where absolutely all agents are subject to DRWR (interpreted to mean that no one will accept a real wage cut), the issue of DNWR becomes moot - except when deflation is expected. Only then will the DNWR mechanism be relevant at values of wage adjustment that exceed the expectation of inflation. Under less stringent conditions, e.g. when the anticipated inflation distribution is not degenerate and contains the point zero, it may be necessary to specify whether DNWR

based on the maximum likelihood approach (e.g. Bauer *et al* (2003) and Barwell and Schweitzer (2004)) assume that some agents are subject to DNWR, some to DRWR, and some to neither type of downward wage rigidity (DWR), specifying the effects of each separately and leaving the overall picture to be determined by an endogenous mixing process. In Christofides and Nearchou (2007), we describe how the 'histogram-location' approach, that goes back to Kahn (1997), can be modified to detect not only DNWR but also DRWR. Our approach makes no parametric assumptions and does not allocate individuals to rigidity regimes, as is inherent in the likelihood-based literature. It does rely, for the identification of possible DRWR effects, on having an inflation experience which is sufficiently diverse to allow the median of the WGD to differ from the centre of the anticipated inflation distribution (AID). As the two points of central tendency drift apart, distortions to the WGD around the mean of the AID (the expected inflation rate or $\dot{P}^e$) may be detected and, if consistent with a priory restrictions, these distortions can be attributed to DRWR. DNWR is still investigated as in Kahn (1997) and Christofides and Leung (2003) by focusing on distortions in the WGD at the point zero. Thus both types of DWR can be examined. Christofides and Nearchou (2007) implement this model using wage contract data from Canada over a period (1976-1999) which is characterised by very high inflation, moderate inflation as well as extremely low inflation; however, it is applicable to any data set with a panel dimension and to any inflation period, provided sufficient care is taken in specifying the model.

In this paper, we extend this earlier work in several directions. First, the histograms are defined such that it is the median of the WGD that is located in the middle of the bin that

or DRWR takes precedence. Suppose, for instance that an agent expects inflation to be -1%, is offered a -3% wage adjustment (i.e. is subject to both a nominal and a real cut); in such a case, will the line of resistance be drawn at zero nominal adjustment (DNWR and an implied anticipated real wage increase of 1%), or at -1% nominal adjustment (DRWR and an implied real wage constancy)? Depending on how the question of which mechanism takes precedence is resolved, this will be reflected in the actual wage adjustment outcomes and the ability to distinguish the processes involved.

contains it, rather than the point zero in its respective bin, as in our earlier paper. In that paper, the focus on zero allowed a neater exploration of the possibility of menu costs. Since this particular type of rigidity mechanism, while statistically significant, appears to account for approximately one percentage point of distortion in the WGD, we now wish to explore a possible lack of clarity that may arise when the median of the WGD is not centred in its so-called 'median' bin for each and every year in the sample. A second issue that we now address is the extent to which the relative frequency approach, used in our earlier work to construct the 'stage 1' bin heights that underlie our 'stage 2' econometric exploration for DWR effects, can be improved by using non-parametric kernel methods. This should be the case on *a priory* grounds, given that the relative frequency approach essentially imposes a zero bandwidth, rather than choosing one optimally. Finally, having dealt with these 'stage 1' issues, we explore the existence of and possible interactions between DNWR and DRWR by paying special attention to inflation sub-periods where (i) one kind of rigidity may be present while the other may not, as in periods of high inflation where DNWR may be not be relevant, (ii) both types of rigidity may be important but DRWR may be more important than DNWR, as in periods of moderate inflation, and (iii) both types or rigidity may be important but DNWR may be more important than DRWR, as during the more recent and prolonged period of extremely low inflation. These explorations raise technical concerns about how the model might be implemented during various sub-periods and they shed light on how these rigidities operate. They also suggest how our approach might be tailored to samples from countries and periods that share generic features with the sub-samples examined here.

Section 2 considers how the notions of DWR are implemented in our work; it also considers each of the three points raised in the previous paragraph, thus better-motivating the contribution of the present paper. Section 3 examines relevant features of the contract data that are used both here and in earlier work; working with the same data base allows useful comparisons. Section 4 presents the econometric specification used and its application to inflation sub-periods. Section 5 presents the results obtained and section 6 summarises our findings and explores possible further work that might be undertaken.

2 Motivating Issues

In all our work this far, we assume that, *if* DNWR holds, agents would be reluctant to accept a nominal wage cut and instead would settle for a nominal wage freeze. At the population level, this reluctance would mean fewer cuts in nominal wages and more nominal wage freezes *relative to* the case of no rigidity. In terms of the distribution of nominal wage growth rates, this translates into a shift of probability mass from negative values of the support of the WGD to the point zero. Therefore the rigidity-contaminated nominal WGD would show a deficit of probability mass for negative values of the support, and a surplus at the point zero, relative to the notional distribution. At the same time, the two distributions should be identical beyond the point zero. Justifications for nominal rigidity range from the comparability and fairness arguments documented in Bewley (1999) to the theoretical papers by MacLeod and Malcomson (1993), Malcomson (1997), Holden (1994), and Holden (2004) which build on the notion that nominal wages can be changed only by mutual consent.

To the extent that agents perceive that small price changes (positive or negative) are not worth the cost of implementing them, some deficit, which may not be symmetric, may appear in the area of the actual WGD immediately below and above zero. In this paper, we still check for these effects when the whole period is considered.

DRWR can be defined in a similar way to DNWR. We assume that DRWR describes the situation where agents are reluctant to accept real-wage cuts but instead would settle for a real-wage freeze. In practice, this attitude takes the form of reluctance towards accepting reductions in the *anticipated* real wage since, at the time of bargaining, future inflation is unknown. As in the case of DNWR, the presence of DRWR would distort the shape of the nominal wage growth distribution. At the population level, this would mean that agents who face nominal wage growth at a rate below anticipated inflation would settle for a nominal wage increase equal to the anticipated rate of inflation. Consequently, the presence of DRWR would shift probability mass to the right, from smaller values of nominal wage growth towards the values of anticipated inflation in the population.

The exact form of the shift of mass to the right towards the values of anticipated inflation depends on the nature of the rigidity mechanism and the joint distribution of the notional (nominal) wage growth and anticipated inflation among all agents. Nevertheless, without any distributional assumptions, it is possible to distinguish three regions in the nominal wage growth distribution for which we can make qualitative predictions about the nature of the distortions. For simplicity, suppose that the support for the AID lies inside that for the WGD. First, the interval of values that lies to the left of the support of the distribution of anticipated inflation could only loose mass to the right since all agents whose nominal wage growth falls in this region face the prospect of a real wage cut. Therefore, in this region, the rigidity-contaminated distribution can only exhibit a deficit. Second, the interval of values that lies to the right of the support of the distribution of anticipated inflation would not be distorted, since all agents whose nominal wage growth falls in this region face the prospect of a real wage increase. Third, the interval of values that corresponds to the support of the distribution of anticipated inflation, will attract mass from its left, and therefore for this interval the rigidity-contaminated distribution will exhibit a surplus in total. However, it is possible that, in some parts of this interval, the rigidity contaminated distribution will exhibit a deficit. In terms of the probability histogram, this is because a particular bin that coincides with values of anticipated inflation can attract mass from bins to its left but at the same time loose mass to bins to its right that also coincide with values of anticipated inflation. The net effect cannot be clear without knowledge of how notional wage growth and anticipated inflation are jointly distributed. The only exception is the rightmost bin in this region, for which we know that it cannot exhibit a deficit since all other bins that contain values of anticipated inflation lie to its left. Despite this uncertainty, we could assume that it would be more likely that bins that lie further to the left in this interval will show a deficit and bins further to the right will show a surplus. The sum of the net effects to the maximum point of the AID support should be zero.

This discussion indicates that the search for DRWR effects is inherently much more difficult than that for DNWR. The distortions arising from DRWR are potentially spread over a wide range of the WGD, beginning with the minimum point of the support and up to the maximum point of the AID. A further complication is that the precise limits of the support of the AID can only be conjectured; it is possible that it extends well to the left and right of $\dot{P}^e$ so that the transfer of mass may involve several bins on either side of $\dot{P}^e$. It is more likely, however, that more bins to the left will be involved than bins to the right given our discussion above.

It is also interesting to note what the presence of DRWR means for the distribution of *actual* real-wage growth. If we accept that typically the AID extends below and above the realised inflation value, then the presence of DRWR is consistent with observing real-wage cuts (relative to the realised value of inflation), even in the case of absolute (i.e. complete reluctance by all to accept a real wage cut) DRWR. Therefore, the occurrence of real-wage cuts does not, in general, suggest that DRWR does not exist; real-wage cuts are inconsistent only with the case of absolute DRWR and perfect foresight.

Having outlined our broad approach to how we expect DWR to impact on the WGD, we now turn to the three main issues that we wish to explore in this paper.

2.1 Centering on the Median

In our earlier work, the wage change information was used, in stage 1, to construct histograms with bins located such that the point zero was at the centre of the bin that contained it, so as to facilitate the exploration of possible menu-cost behaviour. Suppose that, in this zero-based construction, the median of the WGD was only just large enough to enter the so called 'median' bin. Then the bin containing the point zero (at its centre) might be located at the $-j$'th bin, i.e. j bins below the 'median' bin. If, on the other hand, the histograms for each year are constructed with the 'median' bin centered on the actual median for the year, then in the above example the bin containing the point zero (not at its centre) will still be the $-j$'th one. However, any other arbitrary point in the WGD support *could* belong to one bin under the zero-based construction and to an adjacent bin under median centering. An important such point is $\widehat{\dot{P}^e}$, since it figures prominently in our search for DRWR distortions. While, in practice, we do not expect these difficulties to be severe, it is preferable to now construct the yearly histograms by centering on the yearly median. The histograms presented in Figures 1-3 below are indeed constructed in this manner and are very similar with the zero-based ones presented, for selected years, in Christofides and Nearchou (2007).

2.2 Kernel Estimates of Histogram Heights

Our test procedures involve comparisons between the notional (DWR-free) and the actual (rigidity-contaminated) WGD. These comparisons are carried out using probability histograms. We divide the support of the actual WGD into sub-intervals (bins) and compare the amount of probability mass that falls into those intervals (height of bins) to the amount in the corresponding bin of the notional. Bin width selection is driven by the nature of the data and the complexity of distortions that might be involved over intervals.

The bin heights can be formally defined as

$$P_{jt} \equiv Pr\left(\eta_{j,t} \leq \dot{w}_{ti} < \eta_{j+1,t}\right) = Pr\left(\dot{w}_{ti} \in \mathcal{B}_{jt}\right) \tag{1}$$

where $\dot{w}_{ti}$ is the i'th observation in year t, and $\mathcal{B}_{jt} \equiv [\eta_{j,t}, \eta_{j+1,t})$ is the j'th bin of the probability histogram in year t.

In our earlier work, we used relative frequency as the estimator of the height of bins

$$\hat{P}_{jt} \equiv \sum_{i=1}^{n} \frac{I\left(\eta_{j,t} \leq \dot{w}_{ti} < \eta_{j+1,t}\right)}{n} = \sum_{i=1}^{n} \frac{I\left(\dot{w}_{ti} \in \mathcal{B}_{jt}\right)}{n} \tag{2}$$

where $I(\cdot)$ an indicator function. This estimator, which could be motivated from the relative frequency definition of probability, is unbiased as well as consistent. However, in the non-parametric density estimation literature, this estimator is believed to suffer from certain problems. In particular, that it gives non-smooth estimates, that, in addition, depend critically on how the bins are defined, both with respect to their width and location. This is the consequence of the estimator under-smoothing the data.[3]

In this paper we also consider an alternative approach to estimating probability histograms that, in theory, overcomes these problems. It is based on kernel CDF estimation. To motivate the new estimator, we re-write (1) as follows:

$$P_{jt} = F_t\left(\eta_{j+1,t}\right) - F_t\left(\eta_{j,t}\right) \tag{3}$$

where $F_t(\cdot)$ is the CDF for the data in year t. Then, we get an estimator for the bin heights by plugging-in some estimator of the CDF in (3). The CDF estimator we consider is based on the kernel estimator of the corresponding PDF[4]. Substituting $f_t(\cdot)$ in the expression that links the CDF with the PDF by its Kernel estimator, we get

[3]See, for example, Silverman (1986), and Wasserman (2006) for discussion.

[4]See Li and Racine (2007).

$$\hat{F}_t(\dot{w}) = \int_{-\infty}^{\dot{w}} \hat{f}_t(u)\,du$$
$$= \int_{-\infty}^{\dot{w}} \left[\frac{1}{hn}\sum_{i=1}^{n} K\left(\frac{u-\dot{w}_{ti}}{h}\right)\right] du = \frac{1}{n}\sum_{i=1}^{n} G\left(\frac{\dot{w}-\dot{w}_{ti}}{h}\right) \tag{4}$$

where the function $G(\cdot)$ is the integral of the kernel function $K(\cdot)$. The resulting bin height estimator is then given by

$$\hat{P}_{jt} = \frac{1}{n}\sum_{i=1}^{n}\left[G\left(\frac{\eta_{j+1,t}-\dot{w}_{ti}}{h}\right) - G\left(\frac{\eta_{j,t}-\dot{w}_{ti}}{h}\right)\right] \tag{5}$$

This is consistent, but only asymptoticaly unbiased. Furthermore, it coincides with the relative frequency estimator when the bandwidth is set equal to zero.

To apply this estimator, we need to choose the type of kernel function and the bandwidth h. For the work described here we have used the Epanechnikov kernel and the Least Squares Cross Validation method to choose the optimal bandwidth.[5]

2.3 Tailoring the Model to Inflation Sub-Periods

2.3.1 High Inflation (1977-1982)

It is clear that, if inflation is high-enough[6] and the WGD does not involve the point zero, then any specification that allows for DNWR should fail to find it. In our own approach, because the dummy variables that identify bins below zero are nearly always zero in this period, it may be difficult to implement an allowance for DNWR successfully.

Although DRWR distortions are the only ones that should be expected during high-inflation periods, their identification in practice may be difficult if these periods are short in duration

[5] The latter decision is the most critical. The estimation was carried out in R, using the 'np' package. We are grateful to Qi Li for information and to Jeff Racine for code that implements these procedures.

[6] The sub-periods are defined with respect to the values of the estimated mean anticipated inflation, as it is the AID that determines the nature of distortions due to DRWR.

(yielding a small number of observations) and the difference between $\widehat{\dot{P}^e}$ and the median of the WGD is not sufficiently rich. To the extent that any distortions can be identified, these are, most likely, due to DRWR.

2.3.2 Medium Inflation (1983-1991)

During this period, the WGD in our data extends into the negative orthant in every year of the sample. The mass of the actual WGD which is at, or below, zero is as low as 0.7% in 1988 and as high as 11.2% in 1991. At the same time, $\widehat{\dot{P}^e}$ ranges between 3.81% in 1985 and 6.05% in 1983, substantially above the point zero - see section 3 below. Thus, a sizeable distance between the relevant ranges for DNWR and DRWR in the WGD exists and a clear separation and identification of the two processes may be possible.

It is also interesting to explore the importance of misspecifying the estimating equation, as, for instance, when DRWR is ignored while searching for DNWR, as was done in the early papers in this sub-literature.

2.3.3 Low Inflation (1992-1997)

When the median of the WGD is close to zero (as in 1993 and 1994) the extent to which separate DNWR and DRWR can be identified is unclear. The model must be calibrated to avoid undue overlap between DNWR-dedicated and DRWR-dedicated dummy variables. Allowing for too many bins may be inappropriate and it is necessary to also explore the possibility of finer binning.

3 Data Features

The data used in this study is derived from 10,945 collective bargaining agreements reached in all of the industries and regions of Canada between 1996 and 1999.[7] These are legally binding agreements, records for which are kept by Human Resources Development Canada (as it was known at the time the data was released to us), or HRDC. These agreements cover bargaining units involving 200 to nearly 80,000 employees, or approximately 11% of the working population of Canada in the mid year of 1989. They are derived from both the the private and the public sector, and their duration ranges from a few months to several years. Because reporting requirements apply, this information is thought to be very accurate. The data set used in the empirical work below contains one observation from each of the 10,945 contracts which provides the rate of growth of the basic nominal wage rate. This growth rate refers to the total wage adjustment in the contract, including increases occasioned by the cost of living allowance clause ($COLA$). It should be noted, however, that, because the incidence and intensity of $COLA$ clauses is limited throughout the observation period, the results we obtain are similar to those that could be obtained based on non-contingent wage adjustment alone. The observation for each contract is the growth rate of the total nominal-wage adjustment over the whole of the life of the contract, calculated at *annual* rates and is allocated to the year that the contract became effective.

The data from HRDC is supplemented with information from Statistics Canada on the Consumer Price Index (CPI) inflation and an estimate of the mean anticipated inflation ($\widehat{\dot{P}^e}$) for each year.[8] These, along with the median value of the WGD for each year, appear in Table

[7] Because of the small number of contracts involved, the first two and the last three years in the sample are considered together in everything that follows and we refer to these as 'years' 1977 and 1997, respectively.

[8] This is the one-year-ahead forecast from an AR(6) regression model with a GARCH(1,1) error process. This process also supplies the variance of the anticipated inflation rate at each point in time.

1. From the CPI figures, the observation period can be divided into three consecutive periods of inflation: 1977-1983 is a high inflation period with average inflation of 9.58%; 1984-1992 is a medium inflation period with average inflation of 4.67%, and 1993-1997 is a low inflation period with average inflation of 1.46%. There is obviously a positive relationship between the yearly $C\dot{P}I$, $\widehat{\dot{P}^e}$ and the median of the realised WGD. There is also a positive relationship between the level of realised inflation, the spread of anticipated inflation and the spread of the WGDs. The latter is visually evident in Figures 1-3, where the annual histograms of the data are shown.[9] It should be noted that, within each inflation sub-period, the spread of the WGD is relatively constant.

Only 102 (or 0.9%) of the 10,945 contracts in the sample involve nominal-wage cuts, while a substantial number (1142 or 10.4%) show a wage freeze; jointly, these figures could indicate evidence in favour of DNWR. The wage freezes are particularly pronounced during the low inflation years; for each of the years 1993-1996 the proportion of contracts with a wage freeze was above 35%, peaking at 51.0% in 1993. On the other hand, 6045 (or 55.2%) of the contracts exhibit negative real wage growth, while 4801 of them had at the same time positive nominal wage growth. These indications of real wage flexibility must be interpreted with care since they do not rule out DRWR, as has been pointed out. The number of contracts that had exactly zero real wage growth is just 1, and the remaining 4899 (or 44.8%) contracts showed both nominal and real wage increase. The econometric approach used to examine DWR is now described.

4 Empirical Specification

A detailed description of the econometric approach followed in our work appears in Christofides and Nearchou (2007). The basic idea is to test hypotheses about the shape of the actual-

[9]These are median-centered, as discussed in subsection 4.1

wage-growth distribution in terms of the heights of the bars of the corresponding probability histogram. We first proceed to express the actual WGDs for each year into histograms, which are then estimated non-parametrically. The resulting estimates are then used, in a second stage, in econometric estimation, where we estimate jointly the notional distribution and the distortions due to DWR.

4.1 Outline of the testing methodology

Testing for the presence of either type of DWR takes the form of testing hypotheses about the shape of the WGD's. Our approach is to describe the WGD with a probability histogram. Hence, the testing of hypotheses of about the shape of WGDs takes the form of testing hypotheses about the height of the bins of the corresponding probability histogram.

The probability histogram for the WGD of year t could be defined as the collection of probabilities $\{P_{jt}\}_{j=-J}^{J}$, where j is the bin index. Given that our analysis focuses on the shape of the WGDs but not their location, j is defined to indicate the position of the bins relative to each other, rather than the real line. In particular, the bin indexed by $j = 0$ contains the median of the actual wage growth distribution, bins indexed by a negative j lie $|j|$ positions to the left of the median bin and bins indexed by a positive j lie j positions to its right. Furthermore, the bins of the histogram are defined such that that the median is located at the centre of the 'median' bin. We describe the probability histograms defined in this way as 'standardised', using median-centering.

In order to formulate the relevant tests, we parameterise P_{jt} under the hypotheses of no rigidity and DWR respectively by

$$P_{jt} = \begin{cases} p^N\left(z_{jt}^N; b_j^N\right) & \text{, if } H_0 \text{ is true} \\ \\ p^R\left(z_{jt}^R; b_j^R\right) & \text{, if } H_1 \text{ is true} \end{cases} \tag{6}$$

where $p^N(\cdot)$ is the function of a vector of observables z_{jt}^N that gives the height of the j'th bar of the probability histogram of the notional distribution in year t, $p^R(\cdot)$ the function of observables z_{jt}^R that gives the height of the corresponding bar of the probability histogram of the rigidity-contaminated distribution in the same year, and b_j^N and b_j^R the corresponding vectors of parameters. Typically both z_{jt}^N and z_{jt}^R will contain dummy variables that will be functions of j and will indicate the relative position of bin j in the probability histogram; they may also contain additional variables that capture characteristics of the year t, while z_{jt}^R will additionally contain variables that indicate the position of bin j relative to the position of the bins containing the values taken by the rigidity bounds in the population. These variables will be functions of both j and the corresponding indices of the bins that contain the point zero (i.e. the rigidity bound for DNWR), and the anticipated inflation values (i.e. the rigidity bounds for DRWR).

With this formulation, we could test hypotheses about DWR by estimating the unrestricted model (with rigidity), and, subsequently, testing hypotheses, about the parameter vector b_j^R, that imply that the unrestricted model coincides with the restricted (rigidity free). We implement this approach in two stages:

In stage 1, the probability histogram describing the distribution underlying the observed wage growth data for each year in the sample is estimated non-parametrically. In stage 2, for each j, using the set of T estimates of the height of bar j from all years, i.e. $\{\hat{p}_{jt}\}_{t=1,\ldots,T}$, as the set of 'observations' on $\hat{P}_{jt}$,[10] we estimate the regression of $\hat{P}_{jt}$ on the vector of observables z_{jt}^R. When the estimator $\hat{P}_{jt}$ is unbiased, the regression function will coincide with $p^R\left(z_{jt}^R; b_j^R\right)$[11]. Therefore, the estimation of this equation would give estimates of the parameter vector b_j^R and

[10]Now $t = 1, \ldots, T$ becomes the observation index.

[11]Both estimators satisfy this requirement asymptotically, and the relative frequency estimator also in finite samples.

its variance-covariance matrix, enabling us to test a number of restrictions related to DWR. In practice, the regression equations corresponding to all bar heights are estimated jointly since this is typically more efficient.[12]

4.2 Parameterisation of probability histograms

In this section we describe the most general specification of the model for the bin heights, which is estimated with the full sample. For the sub-periods, we trim this specification in order to accommodate for the special features of these periods.

Our chosen parameterisation for the heights of the bars of the probability histograms under the null hypothesis (i.e. for the notional[13] distribution), is the following

$$\begin{aligned} p^N\left(z_{jt}^N; b_j^N\right) &= \beta_{1|j|} + \beta_{2|j|} \times up_{jt} + \left(\beta_{3|j|} + \beta_{4|j|} \times up_{jt}\right) \times m_t \quad , \quad j \neq 0 \\ &= \beta_{10} + \beta_{30} \times m_t \quad , \quad j = 0 \end{aligned} \tag{7}$$

where m_t denotes the median of the actual-wage-growth data in year t, up_{jt} is a dummy variable that is equal to 1 if bin $\mathcal{B}_{jt}$ lies to the right of the bin containing the median ($j > 0$), and the β's are coefficients to be estimated. With this parameterisation the $2J + 1$ probability bars in each histogram can have different height from each other, therefore the notional distribution is not restricted to have any particular shape or to be symmetric. Furthermore, by making the bar height to be a linear function of the location of the actual-wage-growth distribution, and therefore of the location of the notional distribution itself, we allow for the shape of the notional distribution to vary with its location. For example, suppose that the notional distribution is

[12] In such a case, the system would consist of $2J + 1$ equations. The dependent variable corresponding to the equation for a particular observation would be $\hat{P}_{jt}$, where j is the equation index, and t the within equation observation index. To estimate the system we would have in total $(2J + 1) \times T$ observations, with T observations on each equation.

[13] Given the parameterisation of the probability histograms under the alternative discussed below, we take the notional distribution to be the the nominal-wage-growth distribution free of any DWR or menu cost distortions.

symmetric around the bin containing m_t and, further, that its spread increases as its centre moves to higher values.[14] Then $\beta_{2|j|}$ and $\beta_{4|j|}$ will be equal to zero due to the symmetry assumption, $\beta_{1|j|}$ will be non-negative, and $\beta_{3|j|}$ will be negative for the bins in the middle of the distribution, i.e. for small $|j|$, and positive for the bins that lie to the tails of the distribution, i.e. for large $|j|$. Alternatively, if we allow $\beta_{4|j|}$ to be non-zero for some values of j, then the skewness of the notional distribution will also vary with the location.[15]

In order to test for the presence of both types of rigidity, the parameterisation of the probability histogram under the alternative hypothesis should reflect the distortions due to the presence of both. We assume that

$$p^R\left(z_{jt}^R; b_j^R\right) = p^N\left(z_{jt}^N; b_j^N\right) + D^u\left(z_{jt}^u; \mu\right) + D^n\left(z_{jt}^n; \gamma\right) + D^r\left(z_{jt}^r; \delta\right) \text{ , for } R = nr \quad (8)$$

where $D^n\left(z_{jt}^n; \gamma\right)$ is defined to be the difference between the height of the j'th bar of the rigidity-contaminated probability histogram and the height of the corresponding bar of the notional probability histogram in year t that is due to the presence of DNWR, and $D^r\left(z_{jt}^r; \delta\right)$ the corresponding difference that is due to the presence of DRWR. We also allow for distortions due to the presence of menu costs, captured by the term $D^u\left(z_{jt}^u; \mu\right)$.

For distortions due to DNWR we write

$$D^n\left(z_{jt}^n; \gamma\right) = (\gamma_1 + \gamma_2 \times m_t) \times d0_{jt} + (\gamma_3 + \gamma_4 \times m_t) \times dn_{jt} + \gamma_5 \times dz1_{jt} \quad (9)$$

where $d0_{jt}$ is a dummy variable that is equal to 1 if bin $\mathcal{B}_{jt}$ contains the point zero, dn_{jt} a

[14]This would imply a positive relationship between the spread and location of the histograms of the actual-wage-growth data irrespective of whether DWR is present or not.

[15]The assumption in the original Kahn (1997) methodology that the shape of the notional distribution is the same across years, has often been cited as one of the main drawbacks of this methodology as in most actual-wage-growth data sets there appears to exist a variation in the spread of the distribution across years characterised by different levels of inflation. This point is raised by Nickell and Quintini (2003) who go on to propose a flexible way of studying DNWR.

dummy variable that is equal to 1 if bin $\mathcal{B}_{jt}$ is to the left of the bin containing the point zero, and $dz1_{jt}$ a dummy variable that is equal to 1 if bin $\mathcal{B}_{jt}$ is the first bin to the right of the bin that contains the point zero. With the inclusion of the first term we can capture the distortion that applies to the bin that contains zero nominal wage growth, and, with the second term, the distortion that applies to each one of the bins that contain negative values of wage growth. In particular, γ_1 accounts for the distortion associated with the bin that contains zero nominal wage growth and γ_3 the distortion associated with the bins that lie to the left of this bin in the special case where the centre of the notional distribution, which we proxy by m_t, is located at the point zero (i.e. $m_t = 0$). In that case, and, in the presence of DNWR, we would expect γ_1 to be positive, signifying the concentration of probability mass surplus in the zero nominal wage growth bin, and γ_3 negative, signifying the loss of probability mass from the bins that contain negative values of notional wage growth. When the centre of the notional distribution is located further to the right ($m_t > 0$), a smaller part of the left tail of the notional distribution lies below zero, i.e. the proportion of notional wage cuts falls, and, therefore the proportion of notional wage changes that become wage freezes due to DNWR is expected to fall. In that case, γ_2 must be negative, signifying the reduction in the probability mass surplus in the zero nominal wage growth bin, while γ_4 could be either positive or negative or zero, as the amount of mass deficit from each bin containing negative values could change in any direction relative to its level at $m_t = 0$. The inclusion of the last term enables us to test the hypothesis that, apart from shifting mass to the point of zero nominal wage growth, the presence of DNWR could also induce a shift of mass beyond the point zero, towards small positive values (in that case, $\gamma_5 > 0$) - see Holden (1989,1998,2004) and Cramton and Tracy (1992).

The distortion in the height of the probability bar of bin $\mathcal{B}_{jt}$ due to DRWR is assumed to be given by

$$D^r\left(z^r_{jt};\delta\right) = \delta_{1k} + \delta_{2k} \times J^P_t, \quad k = j - J^P_t,\ k_{\min} \leq k \leq k_{\max} \tag{10}$$

$$= \sum_{\nu=k_{\min}}^{k_{\max}} \left(\delta_{1\nu} + \delta_{2\nu} \times J^P_t\right) \times dp_{\nu,jt} \tag{11}$$

where J^P_t is the value of the index of the bin in year t that contains $\widehat{\dot{P}^e}$, k is the distance between bin $\mathcal{B}_{jt}$ and that bin[16], and $dp_{\nu,jt}$ are dummy variables indicating whether bin $\mathcal{B}_{jt}$ is located k positions from the bin that contains the centre of the anticipated-inflation distribution in year t,

$$dp_{\nu,jt} = \begin{cases} 1 & \text{if } \nu = k \left(= j - J^P_t\right) \\ 0 & \text{otherwise} \end{cases} \tag{12}$$

With this specification we allow for the size of the distortions to differ according to the location of the bin in the support of the anticipated-inflation distribution (through the indexing by k), and its location in the support of the notional-wage-growth distribution (through the dependence on J^P_t). In the presence of DRWR, the δ_{1k}'s, which account for the distortion when the centre of the anticipated-inflation distribution is located in the same bin as the median of the actual-wage-growth distribution ($J^P_t = 0$), are expected to be positive for the largest (and positive) values of k and negative for the smallest (and negative) values of k, signifying the shift of probability mass towards the right end of the support of the anticipated-inflation distribution. When J^P_t takes different values, the values of the δ_{2k}'s must be such that the distortions ($\delta_{1k} + \delta_{2k} \times J^P_t$) are qualitatively similar to the case where $J^P_t = 0$, however no specific statements can be made about their sign or size unless specific assumptions are made about the nature of the joint distribution of the notional-wage growth and anticipated inflation, and the rigidity mechanism.

[16]The index k is assumed to take values from the set $\{k_{\min}, \ldots, 0, \ldots, k_{\max}\}$. The bin for which $k = 0$ contains the centre of the anticipated-inflation distribution, bins with positive values of k are located to the right of this bin, and bins with negative values to its left. The values taken by k_{min} and k_{max} are determined empirically.

Finally the effect of menu costs is parameterised as follows

$$D^u\left(z^u_{jt};\mu\right) = \mu \times dnp1_{jt} \tag{13}$$

where $dnp1_{jt}$ is a dummy variable that is equal to 1 if bin $\mathcal{B}_{jt}$ is either one position to the left or to the right of the bin that contains the point zero. Therefore we allow for a symmetric loss of mass ($\mu < 0$) around and close to zero.

For the identification of the parameters of the model it is required that each type of rigidity distort different parts of the wage-growth distribution at least for some of the years in the sample. In this way, there will be sufficient variation in the dummy variables that indicate the bins that are affected by the distortions, so that these will not be collinear with the dummy variables that indicate the position of the bins in the notional probability histogram. This identification strategy is most relevant to the whole sample period where a rich inflation experience can be found. Where sub-periods are concerned, it is important to keep in mind the unique features of the period and to modify the identification strategy.

4.3 Estimation

For the estimation of the probability histograms in stage 1 we consider two alternative estimators; the relative frequency estimator, described by equation (2), and the kernel based estimator, described by equation (5).

Regarding the estimation in stage 2, the exact algebraic expression for the covariance between any pair of estimators that correspond to bins from the same or different probability histograms was derived, for the relative frequency case of stage 1, in Christofides and Nearchou (2007). This allows for the preferred estimator (FGLS) to be implemented but we also reported results based on Ordinary Least Squares (OLS) and the correct covariance matrix (corrected OLS). The relative frequency and Kernel approaches produce stage 1 data that are very similar indeed. However, the covariance matrix for the Kernel approach is not available and so FGLS or corrected OLS could not be implemented. Instead, when we use Kernel stage 1 data, we do so in the context of robust estimation.[17] This yields parameter estimates which are very similar to those obtained with relative frequency data and corrected OLS but the standard errors are larger than they would be under a FGLS procedure.

5 Results

5.1 Whole Sample Results

As the first step, we implemented the model in Christofides and Nearchou (2007) but using the median-centered data discussed above. The results obtained are so similar that, in the interests of economy, are not presented here. In what follows, we always, therefore, use the median-centered data.

A natural next question is whether improvements to the specification of our earlier work can be achieved, given the new median-centered data. Small improvements are possible. In Table 2, we present results for the whole sample, median-centered data, based on FGLS, Corrected OLS, and Kernel-based robust estimation. We have attempted to achieve parsimony in the specification for the effects of DRWR in the area to the right of the bin containing $\widehat{\dot{P}^e}$ because our variance estimates in column 5, Table 1 suggest that the AID is quite tight and because we want to maintain some degree of comparability with specifications for the subperiods. Note that, since DRWR could shift mass from below the minimum point in the support of the AID, similar parsimony to the left of the bin containing $\widehat{\dot{P}^e}$ is not desirable.

It is clear that all the qualitative features of the earlier paper are present. DNWR is clearly present. When the median of the WGD is zero, this type of rigidity accounts for an

[17] The estimator allows for heteroskedasticity, as well as autocorrelation within each year cluster.

accumulation of nearly 9.88 percentage points of mass at the point zero and for a reduction of 1.58 points of mass in each of the bins involving negative wage growth (FGLS). The spike at zero becomes smaller as the median increases; if it were to increase to 4% (the approximate value of the median for the sample as a whole), the additional spike at zero would be 3.72 percentage points ($9.88 - 1.54 \times 4$). It will be seen below that these whole-sample estimates of DNWR average substantially higher effects during the low inflation period with lower effects in the other subperiods. The distortions due to DRWR are well-defined and in line with our expectations: When the 'median' bin also contains $\widehat{\dot{P}^e}$, that bin attracts 3.98 percentage points of additional mass and its adjacent bins about 1.7 percentage points of additional mass (FGLS results), as an approximately equal mass gets shifted from bins further to the left to the bins mentioned above. Again, these are average effects for the whole sample. The Kernel-based coefficient estimates in columns 5, Table 2, are very similar to the Corrected OLS ones; as already noted, the standard errors for this procedure are unduly large. These results are modified by the further interactions and menu cost effects that are allowed for and the rigidity contaminated and notional distributions (FGLS) appear more clearly in Figure 4, for selected years.

The apparent ability of the model to pick up the distortions occasioned by DWR is, to a large extent, due to the rich inflation experience present in the whole sample. It is, now, of interest to see how this model may be applied to the sub-periods. Since these involve fewer observations, it will be necessary to both simplify the model but also to adapt it to suit the needs and challenges of the sub-periods. We simplify by omitting consideration of menu cost behaviour, of changes in the notional distribution, and, of rigidity distortions that may occur as the actual WGD and AID shift around. The latter assumptions are justified by the fact that these shifts are necessarily more limited within the sub-periods. Theses changes reduce substantially the number of parameters that must be estimated during the sub-periods.

5.2 Sub-Samples

5.2.1 High Inflation

During the period 1977-1982, the WGD for the individual years does not often involve negative wage change and DNWR may not be relevant. Table 3 presents FGLS, Corrected OLS and Kernel results for a version of the model that was simplified as described in the previous section. The parameter for DNWR is not significantly different from zero, as one would expect. While the shift of mass towards the bin containing $\widehat{\dot{P}^e}$ is, to an extent, apparent, these distortions are not generally significant. This may be due to the limited number of observations involving diverse points on the WGD. We simplify the model further by imposing symmetry on the notional distribution, an assumption that has been used in several earlier papers. Table 4 shows that significant shifts in mass occur from several points to the left of the bin containing $\widehat{\dot{P}^e}$. The gains in the bin containing $\widehat{\dot{P}^e}$ are statistically significant in the case of the Corrected OLS results, with a gain in the bin containing $\widehat{\dot{P}^e}$ equal to 1.73 percentage points. The Kernel parameter estimates in column 5, Table 4 are similar to those obtained under Corrected OLS, but the standard errors are unduly large. Figure 5 plots the estimated (FGLS) probability histograms for the notional and actual WGDs based on Table 3, and Figure 6 the corresponding histograms based on Table 4.

5.2.2 Medium Inflation

In the period 1983-1991, the inflation rate hovered between approximately 4% and 6%. The WGDs for all years involve negative wage growth and so, in principle, both DNWR and DRWR might be at play. Thus, Table 5 reports a parsimonious version of the model which retains asymmetry in the notional distribution. This model groups the effects on the second to eighth bin below the bin containing $\widehat{\dot{P}^e}$, thus simplifying the estimation (parameter δ_{-128} refers to this group). The results suggest that both kinds of rigidity are at work. For instance, when the median is 4% (its approximate value in this period), the additional mass in the bin containing the point zero is 2.84 percentage points ($11.36 - 2.13 \times 4$), while that in the bin containing the median and the point $\widehat{\dot{P}^e}$ is 6.62 percentage points.

Table 6 and 7 show versions of the model which contain only DNWR and DRWR respectively. These are successfully implemented and suggest quantitatively similar effects for each type of rigidity. Clearly, these results are dominated by those in Table 5, which do not impose any exclusion restrictions.

The Kernel parameter estimates in column 5, of each of Tables 5-7 suggest the same patterns as in earlier tables. Parameter estimates are similar to those obtained under Corrected OLS, but the standard errors are unduly large. Figure 7 plots the estimated (FGLS) probability histograms for the notional and actual WGDs based on Table 5.

5.2.3 Low Inflation

For the more recent, low inflation, period of 1992-1997, we have redesigned the stage 1 data to allow for 0.5 percentage point wide bins so as to have a better chance of capturing the detail between the point zero and the rather low values of anticipated inflation (at most 2.24 in 1995, Table 1). We have also allowed for a more flexible specification for the distortions to the bins with negative values, by replacing the dummy variable dn (equation (9)) with bin specific dummies $dn\zeta$ ($\zeta = 1, \ldots, 6$), where ζ indicates the position of the bin to the left of the bin that contains point zero.[18] Estimates appear in Table 8. The astonishing concentration of mass at the bin containing the point zero is evident in the estimate for the additional height in that bin (this is also the median bin in 1993 and 1994). This bin attracts 36.01 points of additional mass. The DRWR mechanism can also be identified. Mass is shifted from points in the left

[18] The corresponding coefficients are γ_{31} to γ_{36}.

of, to points near and at the bin containing $\widehat{\dot{P}^e}$. For instance, the extra mass at $\widehat{\dot{P}^e}$ is 1.88 percentage points (FGLS). Table 9 suggests that if, as would have been the case in the early years of this literature, a model were fitted for DNWR only, the results (Table 9) would not be unlike those in Table 8.

The Kernel results in columns 5 and 6, Table 8 follow the patterns already noted. Figure 8 plots the estimated (FGLS) probability histograms for the notional and actual WGDs based on Table 8.

6 Conclusion

In this paper, we explored several improvements to the method of constructing the stage 1 histograms that underly the estimation, in stage 2, of DNWR and DRWR distortions. The conceptual improvements produce stage 1 data that are very similar to data from the relative frequency approach. In the stage 2 sub-period estimations, the model performed as expected, failing to find DNWR in the high-inflation period but confirming the existence of distortions due to DNWR and DRWR in the medium and low inflation periods. Particularly challenging has been the identification of DRWR distortions in the high-inflation period.

Future work is planned to explore the high-inflation period further and to determine the covariance matrix for the Kernel approach so as to enable us to achieve reductions in the, currently unduly large, standard errors.

References

[1] Abraham K. G. and J. C. Haltiwanger (1995) Real Wages and the Business Cycle, Journal of Economic Literature, XXXIII, September, 1215-1264.

[2] Altonji, J. G. and P. J. Devereux (2000). The extent and consequences of downward nominal wage rigidity. Research in Labor Economics 19, 383-431.

[3] Barwell, R. and M. Schweitzer (2004). The incidence of nominal and real wage rigidity in Great Britain: 1978-1998. Mimeo, Bank of England.

[4] Bauer, T.K., H. Bonin and U. Sunde (2003). Real and nominal wage rigidities and the rate of inflation: evidence from West German micro data. IZA DP 959.

[5] Bewley, T. F. (1999). Why wages do not fall during a recession? Harvard University Press.

[6] Card, D. and D. Hyslop (1997) Does inflation grease the wheels of the labour market? In C. D. Romer and D. H. Romer (eds) Reducing inflation: Motivation and strategy. NBER, Studies in Business Cycles, 30. University of Chicago Press.

[7] Christofides, L.N. and M.T. Leung (2003). Nominal wage rigidity in contract data: a parametric approach. Economica 70, 619-638.

[8] Christofides, L.N. and T. Stengos (2001). A non-parametric test of the symmetry of the PSID wage-change distribution, Economics Letters, 71: 363-368.

[9] Christofides, L.N. and T. Stengos (2002). The symmetry of the wage-change distribution: survey and contract data, Empirical Economics, 27:705-723.

[10] Christofides, L.N. and T. Stengos (2003). Wage rigidity in Canadian collective bargaining agreements. Industrial and Labor Relations Review 56(3), 429-448.

[11] Christofides L. N. and D. Li (2005). Nominal and real rigidity in a friction model. Economics Letters, 87, 235-241.

[12] Christofides L. N. and P. Nearchou (2007). Real and nominal wage rigidities in collective bargaining agreements. Labour Economics, 14, 695-715.

[13] Cramton, P. and J. S. Tracy (1992). Strikes and holdouts in wage bargaining: theory and data. American Economic Review 82, 100-121.

[14] Crawford A. and A. Harrison (1998) Testing for Downward Rigidity in Nominal Wages, in *Price Stability, Inflation Targets and Monetary Policy*, 179-225, (Ottawa, Bank of Canada).

[15] Dickens, W. and E. Groshen (2004). The International Wage Flexibility Project (IWFP). (Proceedings of the Final Conference, European Central Bank, Frankfurt Am Main, Germany).

[16] Dunlop, J. T. (1938). The movement of real and money wages. Economic Journal, 48, 413-34.

[17] Fortin, P. (1996) The great Canadian Slump. Canadian Journal of Economics, 29, 761-87.

[18] Friedman, M. (1968). The role of mometary policy. American Economic Review 58(1), 1-17.

[19] Holden S. (1989). Wage drift and bargaining: evidence from Norway. Economica 56, 419-432.

[20] Holden S. (1994). Wage bargaining and nominal rigidities. European Economic Review, 38, 1021-1039.

[21] Holden S. (1998). Wage drift and the relevance of centralised wage setting. Scandinavian Journal of Economics 100, 711-731.

[22] Holden S. (2004). The costs of price stability: Downward nominal wage rigidity in Europe. Economica 71, 183-208.

[23] Holden S. and F. Wulfsberg (2007). How Strong is the Case for Downward Real Wage Rigidity? Federal Reserve Bank of Boston, Working Paper No 07-6.

[24] Kahn, S. (1997). Evidence of nominal wage stickiness from microdata. American Economic Review 87, 993-1008.

[25] Li, Q. and J. Racine (2007). *Nonparametric Econometrics.* Princeton University Press.

[26] Lebow, D. E., D. J. Stockton and W. L. Wascher (1995). Inflation, nominal wage rigidity, and the efficiency of labor markets. WP 95-45, Federal Reserve Board, Washington, D.C.

[27] Macleod, W. B. and J. M. Malcomson (1993). Investment, holdup, and the form of market contracts. American Economic Review, 37, 343-354.

[28] Malcomson, J.M. (1997). Contracts, hold-up, and labor markets. Journal of Economic Literature, 35 (4), 1916-1957.

[29] McLaughlin, K.J., 1994, Rigid Wages?, Journal of Monetary Economics 34, 383-414.

[30] Nickell S. J. and G. Quintini (2003). Nominal wage rigidity and the rate of inflation. The Economic Journal 113, 762-781.

[31] Silverman, B.W. (1986). *Density Estimation for Statistics and Data Analysis.* Chapman and Hall.

[32] Smith, J. C. (2000) Nominal wage rigidity in the United Kingdom. Economic Journal, 110, C176-C195.

[33] Solon, G., R. Barsky and J. Parker (1994). Measuring the cyclicality of real wages: how important is composition bias? Quarterly Journal of Economics, 109, 1-25.

[34] Tarshis, L. (1939). Changes in real and money wages. Economic Journal, 49, 150-54.

[35] Wasserman, L. (2006). *All of Nonparametric Statistics.* Springer.

Year	#	$Med(\dot{w}_t)$	CPI	$\widehat{\dot{P}^e}$	$Var\left(\widehat{\dot{P}^e}\right)$
1977	226	8.20	7.55	7.22	0.4217
1978	673	7.43	8.01	8.42	0.4037
1979	569	10.11	8.95	8.45	0.3680
1980	520	11.95	9.13	9.28	0.3307
1981	450	13.10	10.16	11.66	0.3120
1982	562	10.69	12.43	10.43	0.2737
1983	643	5.00	10.80	6.05	0.3342
1984	676	4.00	5.86	4.50	0.3357
1985	519	4.04	4.30	3.81	0.3185
1986	551	4.10	3.96	4.08	0.2682
1987	557	3.83	4.18	4.37	0.2311
1988	556	4.89	4.34	3.97	0.1919
1989	493	5.22	4.05	4.83	0.1236
1990	547	5.77	4.99	4.55	0.1282
1991	530	4.19	4.76	5.91	0.4946
1992	632	2.00	5.62	1.49	0.7411
1993	516	0.00	1.49	2.00	0.4902
1994	471	0.00	1.86	0.50	0.4740
1995	460	0.68	0.16	2.24	0.4620
1996	448	0.87	2.16	1.43	0.4299
1997	346	1.87	1.62	1.95	0.3528
Total	10945				

Table 1: Descriptive statistics.

Parameter	FGLS Estimate	FGLS Std. Err.	OLS-corrected Estimate	OLS-corrected Std. Err.	Kernel Estimate	Kernel Std. Err.
β_{10}	0.3571**	0.0091	0.3055**	0.0110	0.3054**	0.0391
β_{11}	0.1060**	0.0062	0.1963**	0.0103	0.1957**	0.0416
β_{12}	0.0645**	0.0055	0.0883**	0.0094	0.0861*	0.0370
β_{13}	0.0508**	0.0053	0.0788**	0.0082	0.0784*	0.0365
β_{14}	0.0374**	0.0051	0.0513**	0.0073	0.0504†	0.0295
β_{15}	0.0132**	0.0049	0.0535**	0.0062	0.0532*	0.0245
β_{16}	0.0408**	0.0082	0.0518**	0.0048	0.0517**	0.0194
β_{17}	0.0247**	0.0065	0.0538**	0.0039	0.0537**	0.0157
β_{18}	0.0178**	0.0049	0.0560**	0.0039	0.0562**	0.0146
β_{21}	0.1558**	0.0098	0.0345**	0.0126	0.0332	0.0349
β_{22}	0.0133†	0.0080	-0.0101	0.0112	-0.0089	0.0413
β_{23}	-0.0297**	0.0065	-0.0443**	0.0094	-0.0429	0.0392
β_{24}	-0.0359**	0.0053	-0.0414**	0.0077	-0.0406	0.0322
β_{25}	-0.0130*	0.0052	-0.0542**	0.0063	-0.0539*	0.0251
β_{26}	-0.0395**	0.0085	-0.0543**	0.0050	-0.0544**	0.0182
β_{27}	-0.0244**	0.0065	-0.0557**	0.0040	-0.0555**	0.0151
β_{28}	-0.0158**	0.0054	-0.0567**	0.0040	-0.0569**	0.0146
β_{30}	-0.0223**	0.0010	-0.0152**	0.0012	-0.0151**	0.0045
β_{31}	0.0061**	0.0008	-0.0039**	0.0011	-0.0041	0.0038
β_{32}	0.0085**	0.0007	0.0037**	0.0009	0.0038	0.0023
β_{33}	0.0029**	0.0005	-0.0013†	0.0007	-0.0013	0.0017
β_{34}	0.0009*	0.0004	-0.0014*	0.0006	-0.0014	0.0022
β_{35}	0.0015**	0.0004	-0.0019**	0.0006	-0.0019	0.0028
β_{36}	-0.0018*	0.0007	-0.0032**	0.0004	-0.0031*	0.0014
β_{37}	-0.0009†	0.0005	-0.0035**	0.0004	-0.0035**	0.0012
β_{38}	-0.0006	0.0005	-0.0038**	0.0003	-0.0038**	0.0013
β_{41}	-0.0186**	0.0014	-0.0063**	0.0016	-0.0061	0.0039
β_{42}	-0.0060**	0.0012	-0.0013	0.0014	-0.0012	0.0025
β_{43}	0.0004	0.0008	0.0028**	0.0009	0.0028	0.0018
β_{44}	0.0025**	0.0006	0.0041**	0.0008	0.0040	0.0028
β_{45}	0.0003	0.0005	0.0045**	0.0007	0.0046†	0.0026
β_{46}	0.0030**	0.0008	0.0055**	0.0006	0.0055**	0.0012
β_{47}	0.0015**	0.0005	0.0048**	0.0005	0.0048**	0.0013
β_{48}	0.0012*	0.0006	0.0046**	0.0004	0.0046**	0.0013
μ	-0.0134**	0.0026	-0.0221**	0.0016	-0.0219*	0.0094
γ_1	0.0988**	0.0051	0.1615**	0.0102	0.1620**	0.0294
γ_2	-0.0154**	0.0010	-0.0293**	0.0019	-0.0293**	0.0067
γ_3	-0.0158**	0.0017	-0.0603**	0.0038	-0.0603**	0.0136
γ_4	0.0002	0.0004	0.0066**	0.0004	0.0065**	0.0014
γ_5	0.0128**	0.0035	0.0092†	0.0050	0.0088	0.0127
δ_{-18}	-0.0088**	0.0030	-0.0030**	0.0010	-0.0031	0.0045
δ_{-17}	0.0049†	0.0026	0.0021	0.0018	0.0022	0.0080
δ_{-16}	-0.0117**	0.0036	0.0010	0.0037	0.0011	0.0127
δ_{-15}	-0.0168**	0.0041	-0.0034	0.0053	-0.0030	0.0171
δ_{-14}	-0.0268**	0.0044	-0.0186**	0.0067	-0.0178	0.0271
δ_{-13}	-0.0333**	0.0047	-0.0167*	0.0078	-0.0155	0.0314
δ_{-12}	-0.0115*	0.0052	-0.0112	0.0078	-0.0099	0.0341
δ_{-11}	0.0175**	0.0057	-0.0087	0.0073	-0.0079	0.0249
δ_{10}	0.0398**	0.0054	0.0237**	0.0065	0.0247	0.0186
δ_{11}	0.0179**	0.0045	0.0177**	0.0053	0.0178	0.0131
δ_{-28}	0.0076	0.0058	0.0051**	0.0019	0.0052	0.0062
δ_{-27}	0.0009	0.0015	0.0006	0.0020	0.0007	0.0069
δ_{-26}	-0.0023†	0.0012	0.0046*	0.0022	0.0050	0.0072
δ_{-25}	-0.0023*	0.0012	-0.0004	0.0019	-0.0003	0.0071
δ_{-24}	-0.0045**	0.0012	0.0005	0.0018	0.0010	0.0059
δ_{-23}	-0.0075**	0.0014	-0.0015	0.0021	-0.0015	0.0066
δ_{-22}	0.0068**	0.0017	0.0064*	0.0028	0.0066	0.0129
δ_{-21}	0.0157**	0.0024	0.0030	0.0036	0.0024	0.0135
δ_{20}	0.0037	0.0030	-0.0075*	0.0037	-0.0075	0.0105
N	357		357		357	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 2: Estimation results: FULL sample.

Parameter	FGLS Estimate	FGLS Std. Err.	OLS-corrected Estimate	OLS-corrected Std. Err.	Kernel Estimate	Kernel Std. Err.
β_{10}	0.1396**	0.0068	0.1419**	0.0074	0.1424**	0.0163
β_{11}	0.1613**	0.0072	0.1615**	0.0082	0.1590**	0.0158
β_{12}	0.1342**	0.0066	0.1348**	0.0081	0.1334**	0.0266
β_{13}	0.0660**	0.0049	0.0647**	0.0066	0.0639*	0.0282
β_{14}	0.0293**	0.0036	0.0310**	0.0055	0.0309	0.0253
β_{15}	0.0114**	0.0027	0.0262**	0.0053	0.0252	0.0287
β_{16}	0.0089**	0.0025	0.0089*	0.0044	0.0087	0.0123
β_{17}	0.0052*	0.0021	0.0041	0.0042	0.0029	0.0070
β_{18}	0.0055†	0.0028	0.0009	0.0031	0.0006	0.0027
β_{21}	-0.0311**	0.0096	-0.0426**	0.0103	-0.0423†	0.0223
β_{22}	-0.0180*	0.0090	-0.0240*	0.0103	-0.0217	0.0205
β_{23}	-0.0035	0.0066	-0.0071	0.0083	-0.0051	0.0305
β_{24}	0.0145**	0.0052	0.0109	0.0069	0.0107	0.0281
β_{25}	0.0216**	0.0041	0.0067	0.0064	0.0082	0.0285
β_{26}	0.0168**	0.0037	0.0161**	0.0055	0.0164	0.0133
β_{27}	0.0062*	0.0028	0.0106*	0.0049	0.0115	0.0086
β_{28}	0.0040	0.0033	0.0082*	0.0037	0.0083**	0.0025
γ_1	-0.0006	0.0033	-0.0017	0.0045	-0.0007	0.0072
δ_{-18}	-0.0019	0.0033	0.0062	0.0052	0.0064	0.0059
δ_{-17}	0.0065†	0.0036	0.0025	0.0038	0.0031	0.0023
δ_{-16}	-0.0010	0.0023	0.0021	0.0043	0.0023	0.0042
δ_{-15}	-0.0004	0.0024	0.0096*	0.0046	0.0103	0.0068
δ_{-14}	-0.0031	0.0025	-0.0093†	0.0050	-0.0089	0.0160
δ_{-13}	-0.0046	0.0031	-0.0158**	0.0057	-0.0149	0.0188
δ_{-12}	-0.0047	0.0036	0.0011	0.0070	0.0029	0.0358
δ_{-11}	-0.0047	0.0057	-0.0049	0.0079	-0.0040	0.0333
δ_{10}	0.0086	0.0073	0.0068	0.0084	0.0076	0.0241
δ_{11}	0.0011	0.0074	0.0039	0.0083	0.0049	0.0135
N	102		102		102	

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 3: Estimation results: HIGH inflation period (Model 1).

Parameter	FGLS Estimate	FGLS Std. Err.	OLS-corrected Estimate	OLS-corrected Std. Err.	Kernel Estimate	Kernel Std. Err.
β_{10}	0.1435**	0.0067	0.1368**	0.0072	0.1378**	0.0211
β_{11}	0.1486**	0.0046	0.1353**	0.0052	0.1334**	0.0127
β_{12}	0.1302**	0.0043	0.1189**	0.0048	0.1191**	0.0098
β_{13}	0.0689**	0.0030	0.0586**	0.0034	0.0593**	0.0079
β_{14}	0.0396**	0.0023	0.0362**	0.0027	0.0364**	0.0040
β_{15}	0.0222**	0.0018	0.0313**	0.0025	0.0314**	0.0079
β_{16}	0.0184**	0.0017	0.0203**	0.0021	0.0206**	0.0025
β_{17}	0.0108**	0.0013	0.0134**	0.0018	0.0130**	0.0025
β_{18}	0.0100**	0.0014	0.0086**	0.0014	0.0085**	0.0030
γ_1	-0.0010	0.0032	-0.0013	0.0045	-0.0003	0.0084
δ_{-18}	-0.0058†	0.0031	-0.0025	0.0042	-0.0028	0.0123
δ_{-17}	0.0036	0.0033	-0.0067**	0.0021	-0.0065	0.0076
δ_{-16}	-0.0065**	0.0017	-0.0065*	0.0025	-0.0069	0.0068
δ_{-15}	-0.0058**	0.0021	0.0013	0.0029	0.0014	0.0155
δ_{-14}	-0.0113**	0.0019	-0.0143**	0.0027	-0.0148**	0.0035
δ_{-13}	-0.0138**	0.0025	-0.0166**	0.0037	-0.0166**	0.0050
δ_{-12}	-0.0133**	0.0030	0.0084	0.0053	0.0092	0.0241
δ_{-11}	-0.0065	0.0051	0.0058	0.0069	0.0056	0.0184
δ_{10}	0.0080	0.0071	0.0173*	0.0080	0.0173	0.0240
δ_{11}	-0.0022	0.0073	0.0086	0.0081	0.0091	0.0206
N	102		102		102	

Significance levels : † : 10% $*$: 5% $**$: 1%

Table 4: Estimation results: HIGH inflation period (Model 2).

Parameter	FGLS Estimate	FGLS Std. Err.	OLS-corrected Estimate	OLS-corrected Std. Err.	Kernel Estimate	Kernel Std. Err.
β_{10}	0.2347**	0.0073	0.2529**	0.0086	0.2534**	0.0310
β_{11}	0.1452**	0.006	0.1892**	0.0085	0.1888**	0.0210
β_{12}	0.0992**	0.0045	0.1259**	0.0075	0.1256**	0.0218
β_{13}	0.0376**	0.0028	0.0861**	0.0074	0.0872**	0.0298
β_{14}	0.017**	0.0023	0.0525**	0.0069	0.0526*	0.0267
β_{15}	0.009*	0.0036	0.0352**	0.0067	0.0355	0.0262
β_{16}	0.0332**	0.0083	0.0398**	0.0065	0.0400	0.0268
β_{21}	0.0606**	0.0089	0.0067	0.0102	0.0061	0.0272
β_{22}	-0.0259**	0.0061	-0.0516**	0.0083	-0.0505*	0.0252
β_{23}	-0.0058	0.0038	-0.0533**	0.0078	-0.0542†	0.0287
β_{24}	-0.0024	0.0028	-0.0377**	0.0072	-0.0381	0.0270
β_{25}	-0.0039	0.0037	-0.0298**	0.0068	-0.0299	0.0250
β_{26}	-0.0295**	0.0083	-0.0357**	0.0066	-0.0360	0.0258
γ_1	0.1136**	0.0196	0.1381**	0.0209	0.1387*	0.0677
γ_2	-0.0213**	0.0045	-0.0211**	0.0042	-0.0212	0.0137
δ_{-128}	-0.0045**	0.0016	-0.0387**	0.0066	-0.0390	0.0266
δ_{-11}	0.0309**	0.0068	-0.0042	0.009	-0.0043	0.0198
δ_{10}	0.0662**	0.0078	0.0277**	0.0088	0.0293	0.0183
δ_{11}	0.0215**	0.0054	0.0197**	0.0069	0.0182	0.0196
N	117		117		117	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 5: Estimation results: MEDIUM inflation period (Model 1).

Parameter	FGLS Estimate	FGLS Std. Err.	OLS-corrected Estimate	OLS-corrected Std. Err.	Kernel Estimate	Kernel Std. Err.
β_{10}	0.2743**	0.0058	0.2643**	0.0061	0.2652**	0.0254
β_{11}	0.1674**	0.0049	0.1806**	0.0054	0.1804**	0.0222
β_{12}	0.1045**	0.0040	0.0949**	0.0041	0.0943**	0.0090
β_{13}	0.0337**	0.0024	0.0474**	0.0030	0.0482**	0.0106
β_{14}	0.0130**	0.0017	0.0138**	0.0021	0.0136**	0.0035
β_{15}	0.0009	0.0021	-0.0035**	0.0011	-0.0035	0.0034
β_{16}	0.0232**	0.0075	0.0011**	0.0004	0.0011	0.0016
β_{21}	0.0705**	0.0082	0.0298**	0.0088	0.0287	0.0308
β_{22}	-0.0206**	0.0056	-0.0131*	0.0059	-0.0120	0.0189
β_{23}	0.0006	0.0034	-0.0124**	0.0040	-0.0132	0.0134
β_{24}	0.0019	0.0023	0.0010	0.0027	0.0009	0.0048
β_{25}	0.0040	0.0024	0.0089**	0.0015	0.0091*	0.0039
β_{26}	-0.0196**	0.0075	0.0030**	0.0010	0.0030	0.0024
γ_1	0.0882**	0.0171	0.1381**	0.0209	0.1387*	0.0664
γ_2	-0.0153**	0.0039	-0.0211**	0.0042	-0.0212	0.0134
N	117		117		117	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 6: Estimation results: MEDIUM inflation period (Model 2).

Parameter	FGLS Estimate	FGLS Std. Err.	OLS-corrected Estimate	OLS-corrected Std. Err.	Kernel Estimate	Kernel Std. Err.
β_{10}	0.2367**	0.0073	0.2529**	0.0086	0.2534**	0.0307
β_{11}	0.1445**	0.006	0.1892**	0.0085	0.1888**	0.0208
β_{12}	0.0972**	0.0045	0.1259**	0.0075	0.1256**	0.0215
β_{13}	0.0343**	0.0027	0.0861**	0.0074	0.0872**	0.0295
β_{14}	0.0172**	0.0022	0.082**	0.0076	0.0822**	0.0276
β_{15}	0.0046†	0.0026	0.0458**	0.0067	0.0461	0.0308
β_{16}	0.0086*	0.0037	0.0416**	0.0065	0.0418	0.0256
β_{21}	0.0642**	0.0089	0.0067	0.0102	0.0061	0.0269
β_{22}	-0.0227**	0.0061	-0.0516**	0.0083	-0.0505*	0.0249
β_{23}	-0.002	0.0037	-0.0533**	0.0078	-0.0542†	0.0284
β_{24}	-0.0023	0.0027	-0.0672**	0.0079	-0.0676*	0.0281
β_{25}	-0.0014	0.0028	-0.0404**	0.0068	-0.0405	0.0295
β_{26}	-0.005	0.0037	-0.0375**	0.0065	-0.0378	0.0246
δ_{-128}	-0.0005	0.0014	-0.0387**	0.0066	-0.0390	0.0263
δ_{-11}	0.0348**	0.0067	-0.0042	0.009	-0.0043	0.0196
δ_{10}	0.0693**	0.0078	0.0277**	0.0088	0.0293	0.0181
δ_{11}	0.0225**	0.0054	0.0197**	0.0069	0.0182	0.0194
N	117		117		117	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 7: Estimation results: MEDIUM inflation period (Model 3).

Parameter	FGLS Estimate	FGLS Std. Err.	OLS-corrected Estimate	OLS-corrected Std. Err.	Kernel Estimate	Kernel Std. Err.
β_{10}	0.1377**	0.0085	0.1490**	0.0094	0.1485**	0.0277
β_{11}	0.0969**	0.0054	0.1143**	0.0090	0.1143**	0.0220
β_{12}	0.0791**	0.0043	0.1110**	0.0074	0.1108**	0.0186
β_{13}	0.0640**	0.0038	0.0544**	0.0046	0.0547**	0.0054
β_{14}	0.0471**	0.0034	0.0444**	0.0043	0.0449**	0.0086
β_{15}	0.0390**	0.0033	0.0400**	0.0027	0.0403**	0.0060
β_{16}	0.0242**	0.0025	0.0218**	0.0022	0.0216*	0.0094
β_{17}	0.0053**	0.0016	0.0041*	0.0017	0.0039	0.0034
β_{18}	0.0010	0.0014	-0.0058**	0.0015	-0.0058	0.0074
β_{21}	-0.0191*	0.0076	-0.0219*	0.0105	-0.0222	0.0247
β_{22}	0.0417**	0.0080	0.0171†	0.0100	0.0172	0.0154
β_{23}	0.0063	0.0062	0.0232**	0.0069	0.0230	0.0153
β_{24}	-0.0069	0.0052	-0.0008	0.0057	-0.0006	0.0127
β_{25}	-0.0174**	0.0043	-0.0025	0.0045	-0.0021	0.0143
β_{26}	-0.0125**	0.0032	0.0069†	0.0038	0.0066	0.0130
β_{27}	-0.0001	0.0020	0.0012	0.0022	0.0010	0.0034
β_{28}	0.0024	0.0017	0.0217**	0.0025	0.0213	0.0158
γ_1	0.3601**	0.0113	0.3159**	0.0165	0.3155**	0.0431
γ_2	-0.1213**	0.0074	-0.1169**	0.0109	-0.1166**	0.0204
γ_{36}	-0.0199**	0.0022	-0.0201**	0.0021	-0.0199**	0.0068
γ_{35}	-0.0260**	0.0046	-0.0315**	0.0029	-0.0318**	0.0040
γ_{34}	-0.0455**	0.0034	-0.0475**	0.0036	-0.0471**	0.0059
γ_{33}	-0.0601**	0.0041	-0.0614**	0.0044	-0.0613**	0.0068
γ_{32}	-0.0748**	0.0043	-0.0860**	0.0059	-0.0864**	0.0135
γ_{31}	-0.0965**	0.0056	-0.1121**	0.0076	-0.1126**	0.0139
γ_4	0.0246**	0.0017	0.0294**	0.0021	0.0295**	0.0028
δ_{-15}	0.0042	0.0029	0.0054*	0.0027	0.0057	0.0047
δ_{-14}	0.0102**	0.0034	0.0241**	0.0071	0.0240†	0.0126
δ_{-13}	0.0040	0.0049	0.0067	0.0066	0.0066	0.0151
δ_{-12}	0.0207**	0.0054	0.0085	0.0072	0.0085	0.0235
δ_{-11}	0.0167*	0.0075	-0.0166†	0.0086	-0.0166	0.0208
δ_{10}	0.0188**	0.0061	0.0027	0.0071	0.0029	0.0219
δ_{11}	0.0193**	0.0062	-0.0028	0.0070	-0.0026	0.0183
N	102		102		102	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 8: Estimation results: LOW inflation period (Model 1).

Parameter	FGLS Estimate	FGLS Std. Err.	OLS-corrected Estimate	OLS-corrected Std. Err.	Kernel Estimate	Kernel Std. Err.
β_{10}	0.1524**	0.0076	0.1449**	0.0086	0.1444**	0.0262
β_{11}	0.1075**	0.0044	0.1141**	0.007	0.1141**	0.0152
β_{12}	0.087**	0.0037	0.1081**	0.0069	0.1081**	0.0110
β_{13}	0.0744**	0.0032	0.0625**	0.0041	0.0628**	0.0085
β_{14}	0.0545**	0.0031	0.0457**	0.0042	0.0455**	0.0105
β_{15}	0.0473**	0.0028	0.0411**	0.0025	0.0411**	0.0069
β_{16}	0.0276**	0.0024	0.0219**	0.0021	0.0223**	0.0074
β_{17}	0.0061**	0.0016	0.0037*	0.0017	0.0036	0.0023
β_{18}	0.0013	0.0014	-0.0061**	0.0015	-0.0057	0.0065
β_{21}	-0.0185**	0.0071	-0.0186†	0.0097	-0.0187	0.0223
β_{22}	0.0496**	0.0075	0.0178†	0.01	0.0177	0.0152
β_{23}	0.0023	0.006	0.0128†	0.0067	0.0132	0.0129
β_{24}	-0.0086†	0.0049	-0.002	0.0058	-0.0023	0.0105
β_{25}	-0.0245**	0.0039	-0.0041	0.0044	-0.0046	0.0152
β_{26}	-0.0158**	0.0031	0.0068†	0.0038	0.0071	0.0133
β_{27}	-0.0009	0.002	0.0016	0.0022	0.0020	0.0020
β_{28}	0.0022	0.0017	0.022**	0.0025	0.0217	0.0156
γ_{1}	0.3838**	0.01	0.3269**	0.0157	0.3264**	0.0456
γ_{2}	-0.1375**	0.0067	-0.1147**	0.0107	-0.1143**	0.0293
γ_{36}	-0.0229**	0.0021	-0.02**	0.0021	-0.0205**	0.0052
γ_{35}	-0.0328**	0.0043	-0.0321**	0.0027	-0.0324**	0.0059
γ_{34}	-0.0522**	0.003	-0.0473**	0.0034	-0.0469**	0.0076
γ_{33}	-0.0683**	0.0036	-0.0606**	0.0039	-0.0605**	0.0073
γ_{32}	-0.0832**	0.0038	-0.0839**	0.0053	-0.0836**	0.0116
γ_{31}	-0.1006**	0.0043	-0.1014**	0.0057	-0.1019**	0.0128
γ_{4}	0.0273**	0.0015	0.0296**	0.0019	0.0298**	0.0031
N	102		102		102	

Significance levels : † : 10% ∗ : 5% ∗∗ : 1%

Table 9: Estimation results: LOW inflation period (Model 2).

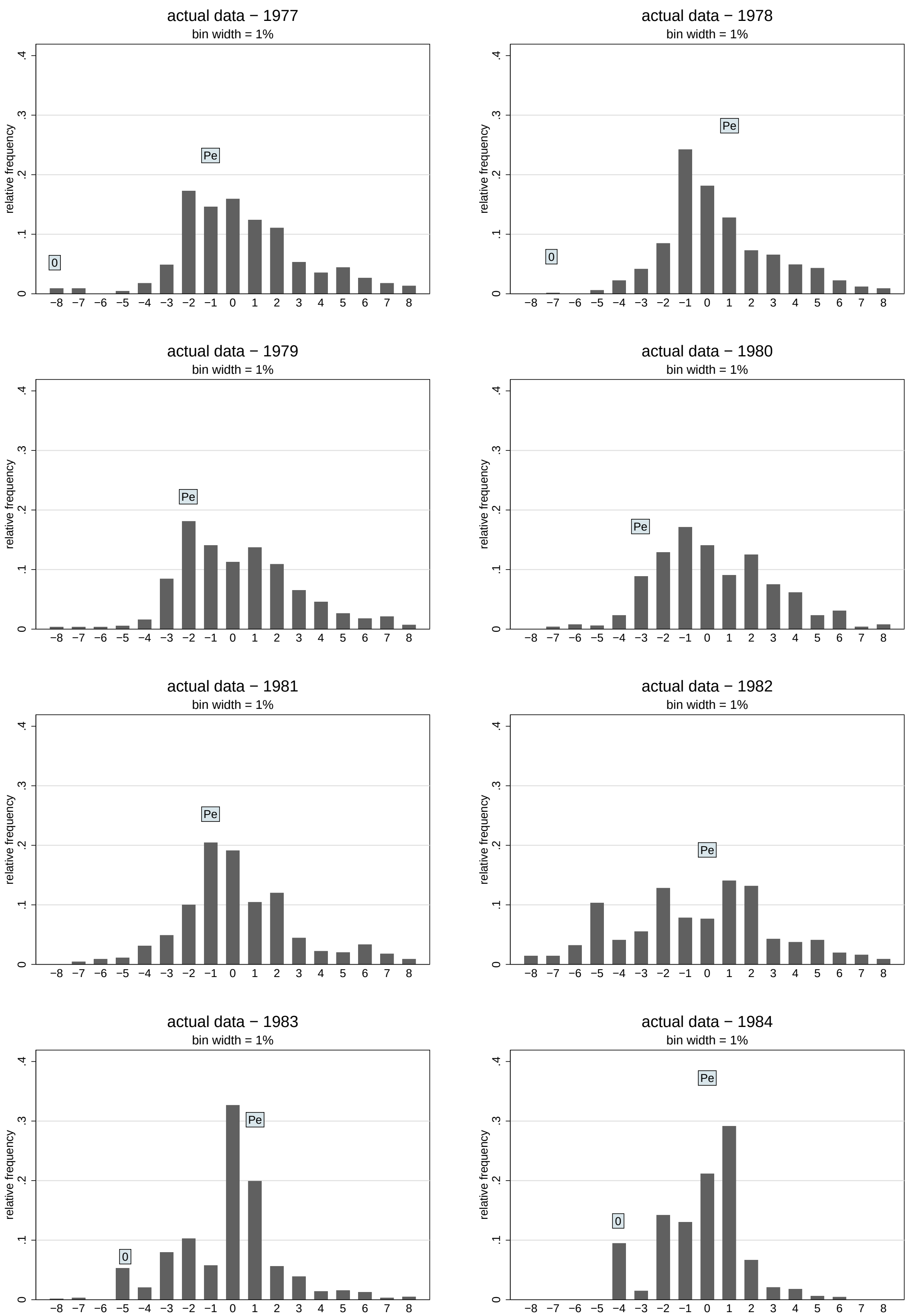

Figure 1: Standardised (median-centred) relative frequency histograms.

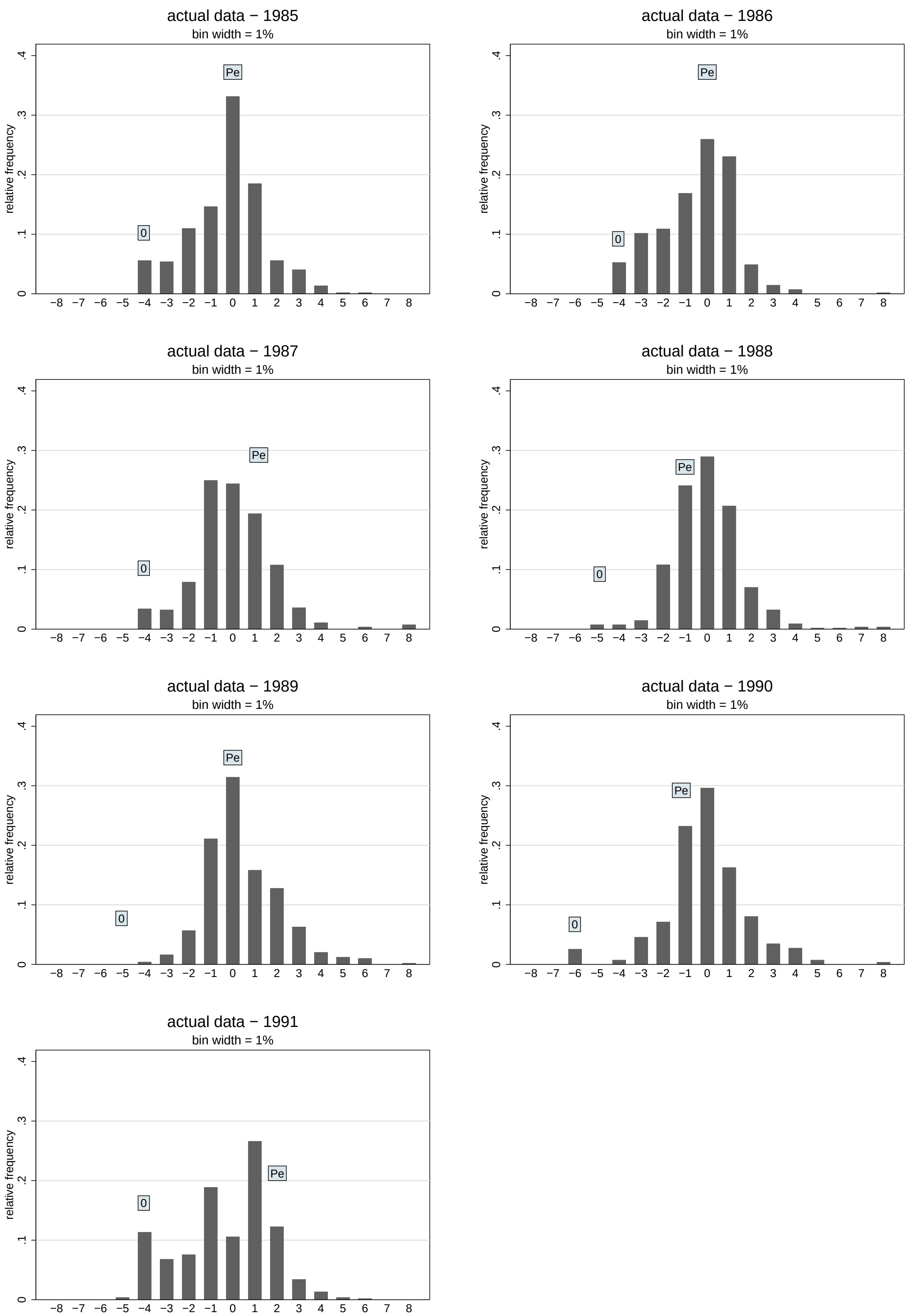

Figure 2: Standardised (median-centred) relative frequency histograms.

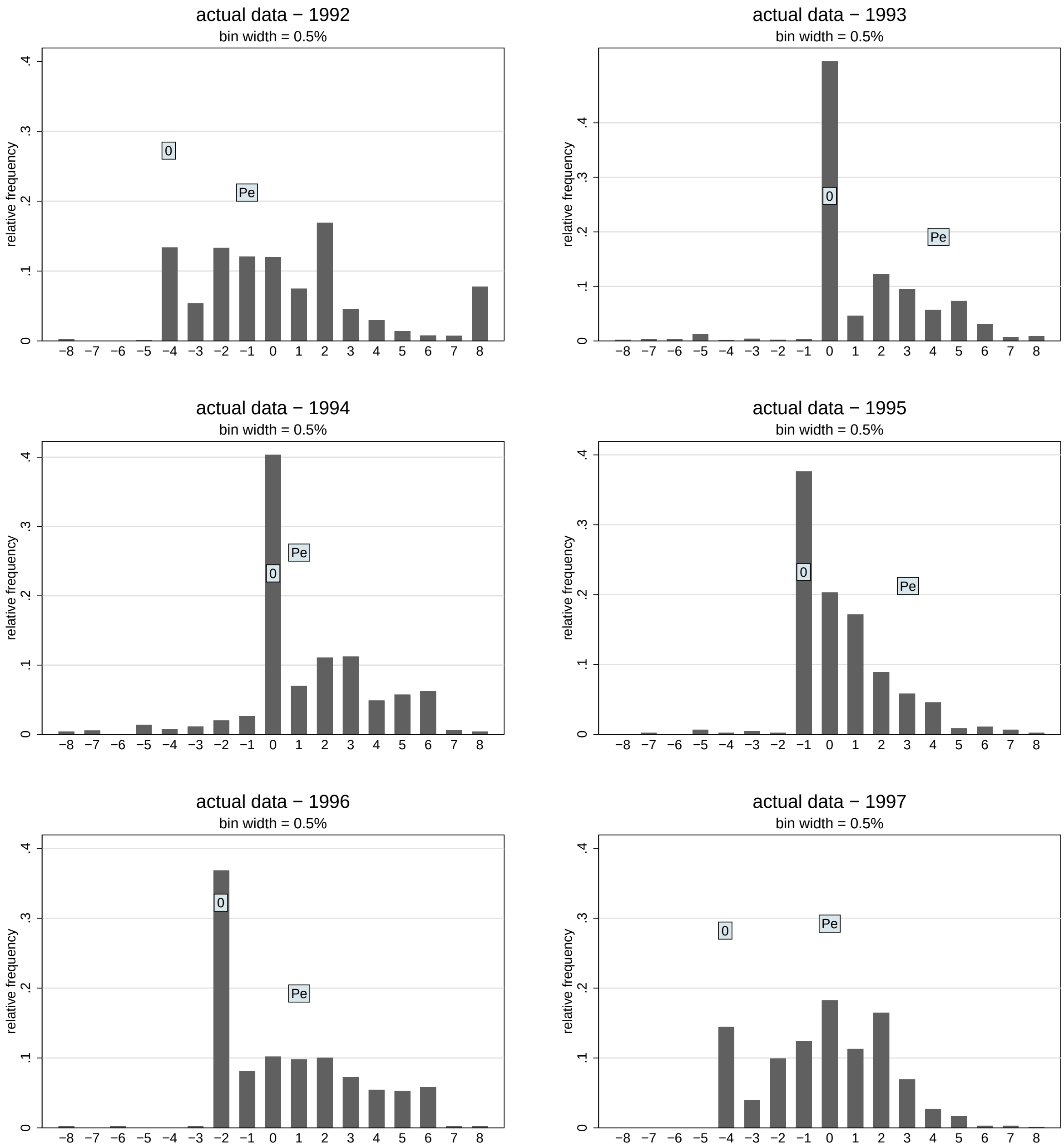

Figure 3: Standardised (median-centred) relative frequency histograms.

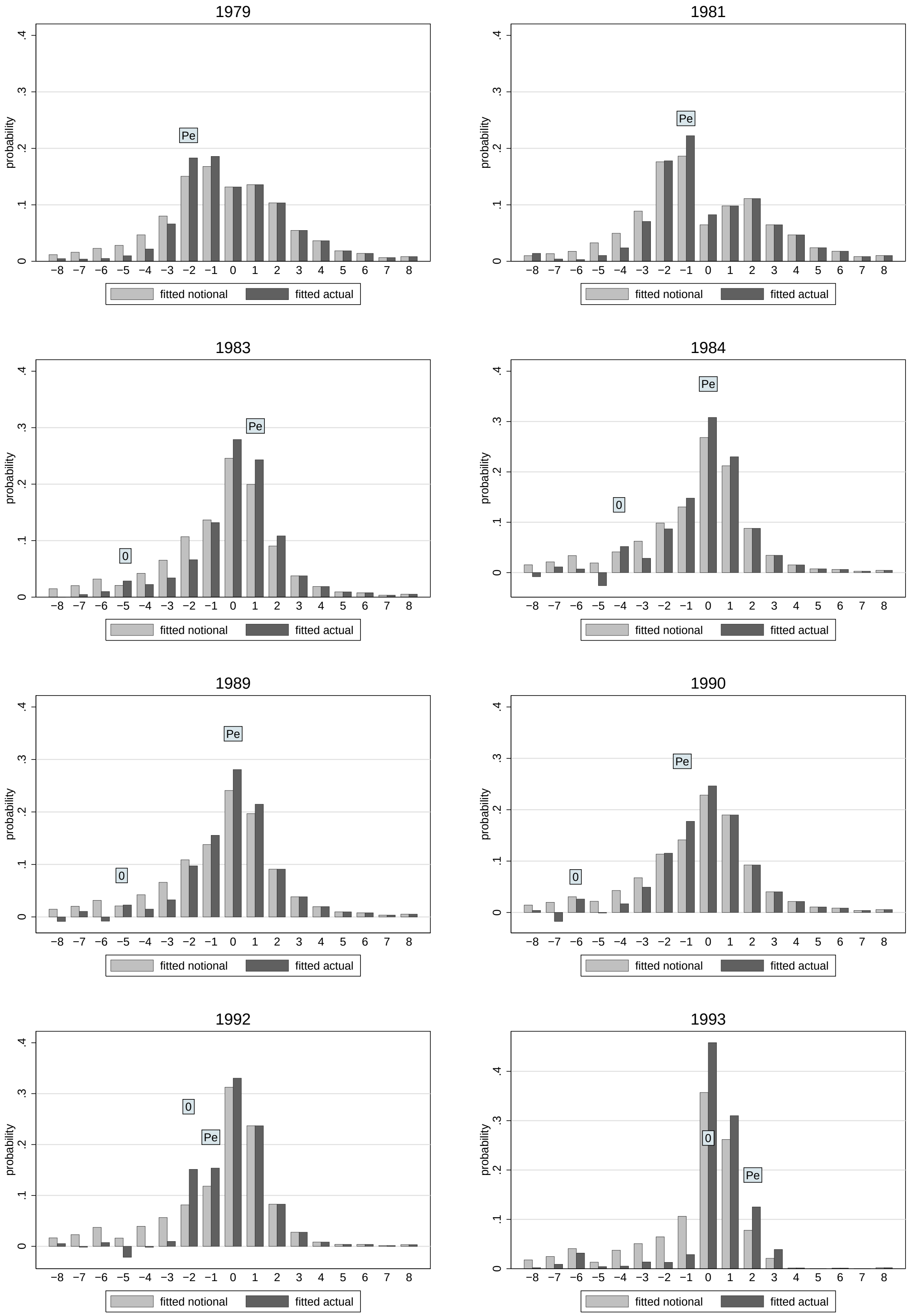

Figure 4: Fitted values of Notional Vs Actual nominal-wage-growth distributions: FULL sample (diagrams for selected years).

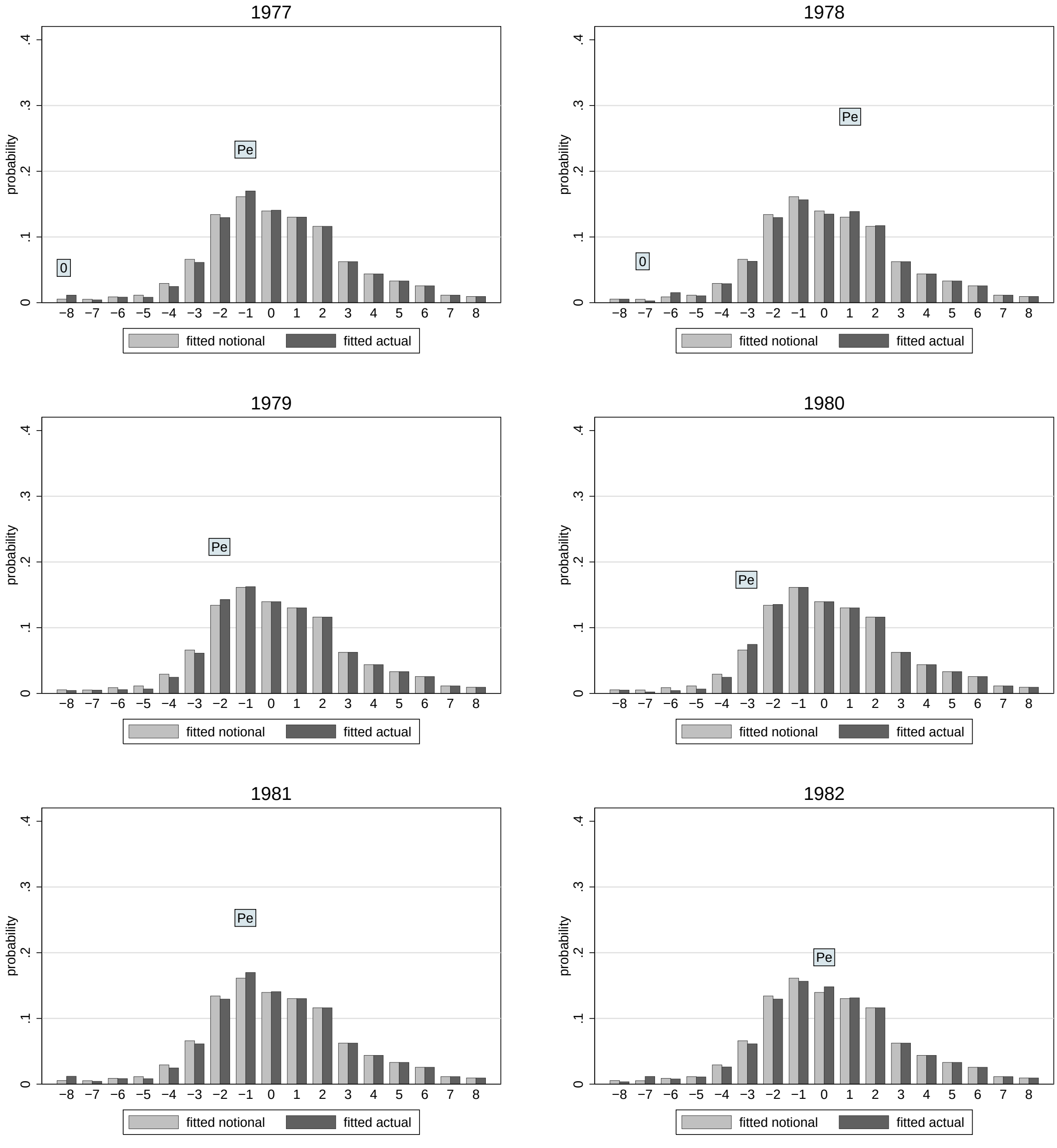

Figure 5: Fitted values of Notional Vs Actual nominal-wage-growth distributions: HIGH inflation period (Model 1).

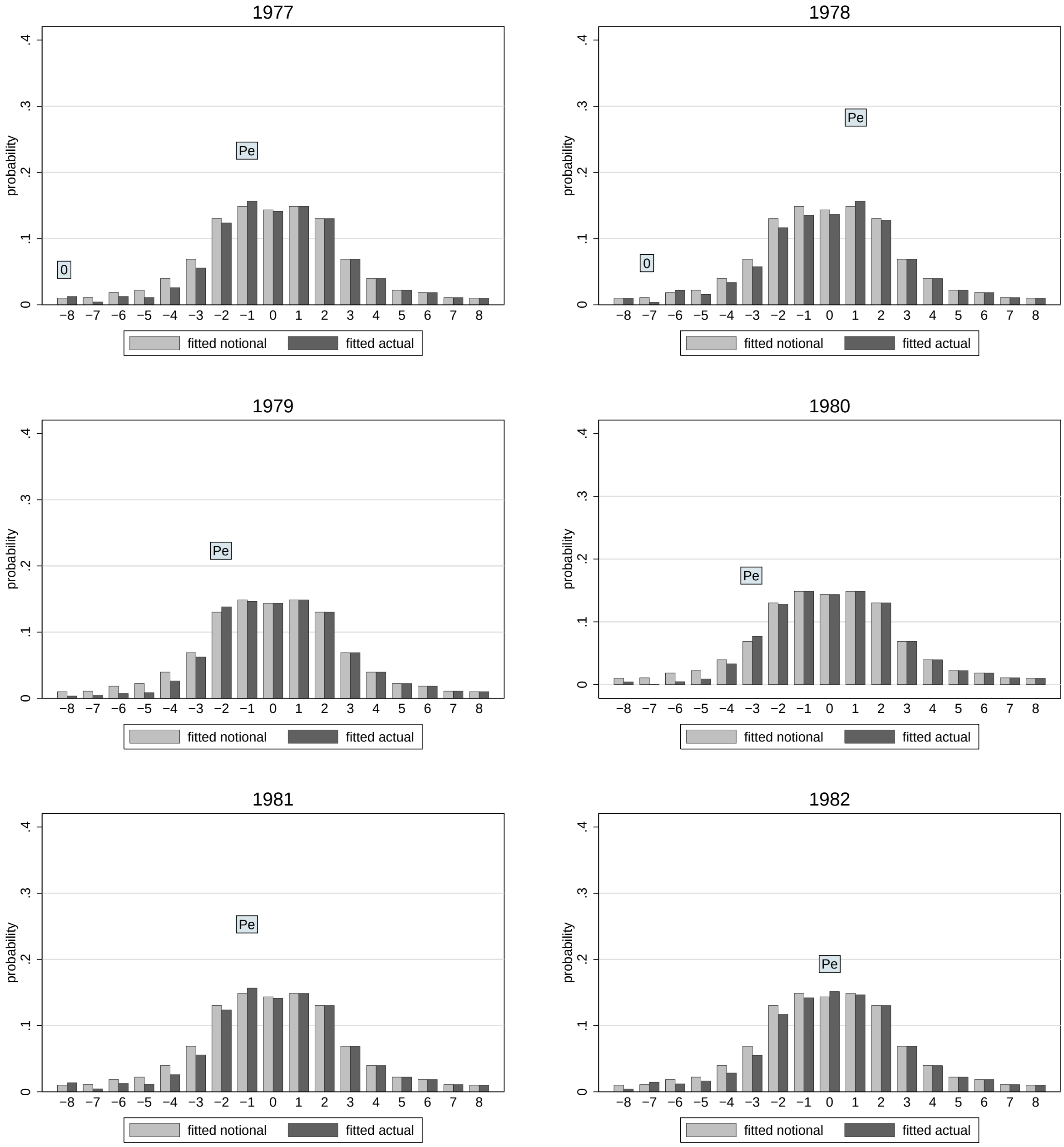

Figure 6: Fitted values of Notional Vs Actual nominal-wage-growth distributions: HIGH inflation period (Model 2).

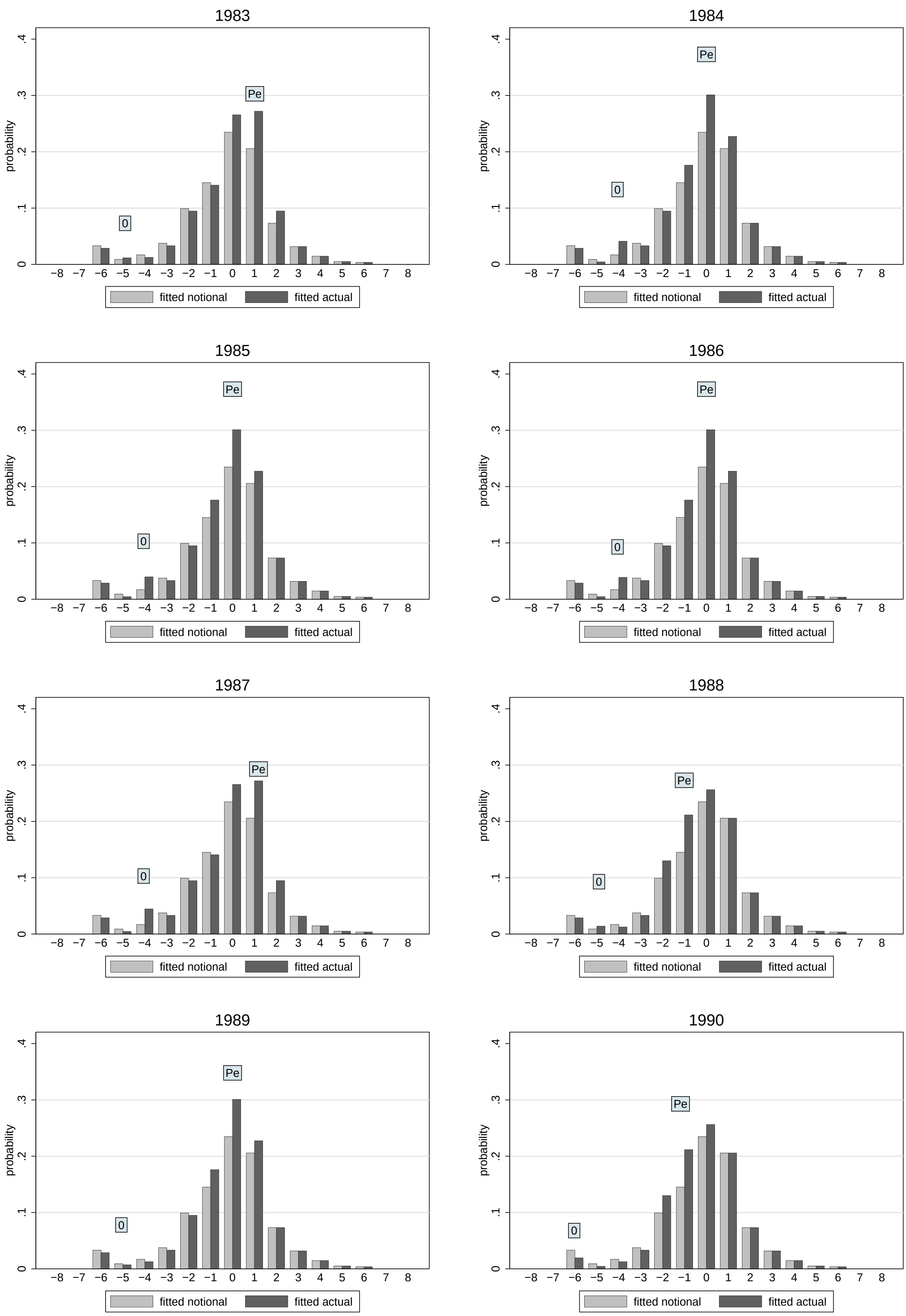

Figure 7: Fitted values of Notional Vs Actual nominal-wage-growth distributions: MEDIUM inflation period (Model 1).

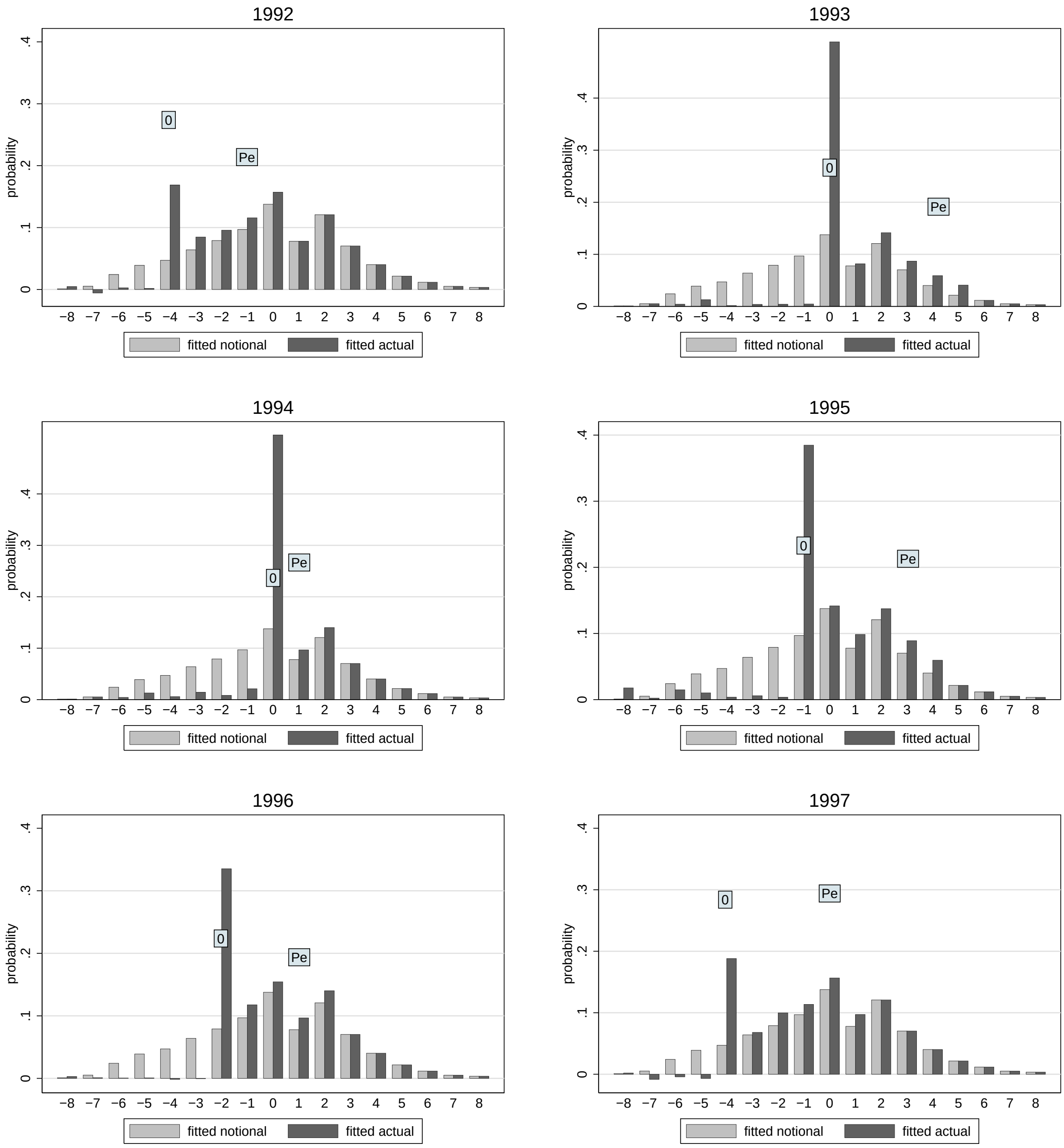

Figure 8: Fitted values of Notional Vs Actual nominal-wage-growth distributions: LOW inflation period (Model 1).