Real and Nominal Wage Rigidities in Collective Bargaining Agreements

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Abstract

An earlier study of wage agreements, reached in the Canadian unionized sector between 1976-99, found that wage adjustment is characterized by downward nominal rigidity and significant spikes at zero. We extend this earlier approach to encompass the possibility of real as well as nominal wage rigidity. The addition of real wage rigidity variables enhances earlier results and suggests that real rigidity increases significantly the mass in the histogram bin containing the mean expected rate of inflation, as well as in adjacent bins. Downward nominal wage rigidities and spikes at zero remain important.

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1 Introduction

Monetary policies in a number of countries have, at least until the current oil price shock, succeeded in limiting price inflation. A by-product of this success has been concern with the extent to which this inflation record has been achieved at a cost. In a low inflation environment, downward nominal wage rigidity (DNWR) may mean that nominal wage reductions, called for by bargaining pair-specific productivity shocks, do not occur, thereby compromising the efficiency of the labour market. Indeed, some studies go as far as to look for the unemployment consequences of such low-inflation mechanisms. If inflation greases the wheels of the labor market, then its absence may lead to costs. An expanding literature covering a number of countries takes advantage of the recent periods of low price inflation and attempts to measure the extent and consequences of DNWR.[1] This literature has been further energized by the International Wage Flexibility Project (IWFP), led by William Dickens and Erica Groshen.[2]

An important concern of studies in this literature should be the extent to which real rigidities can be treated as part and parcel of the more general wage adjustment process. Naturally, the extent to which price inflation and particularly expected price inflation feed into nominal wage adjustment is a subject that goes, through Friedman (1968), at least as far back as Phillips (1958). While nominal wage adjustment is clearly conditioned by price inflation effects, the extent to which downward real wage rigidity (DRWR) exists, its implied impact on the shape of the wage adjustment distribution in the neighborhood of the expected rate of inflation, and possible interactions of this process with DNWR are issues that deserve further attention.

A particularly good data set for studying these effects is the Human Resources Development Canada (HRDC) record of the provisions of collective bargaining agreements reached in the Canadian unionised sector. The data is thought to be very accurate because it refers to legally

[1] An extensive review of the literature is contained in Christofides and Leung (2003).

[2] Much more information is provided in the proceedings of the project's Final Conference (June 17-18, 2004).

binding provisions, it covers all industries over all of Canada, and it covers high as well as low inflation periods since 1976. In an earlier paper by Christofides and Leung (2003), the HRDC data were used to examine DNWR and menu cost behaviour in the period 1976-1999 using parametric techniques inspired by Kahn (1997). In this paper, we extend the earlier study to more explicitly encompass DRWR and its interaction with DNWR.[3] A strength of the HRDC data for current purposes is that the diverse inflation experience that it encompasses makes it possible to differentiate DNWR from DRWR processes. The results obtained indicate significant and substantial nominal and real wage rigidity in the contract data.

The rest of the paper is organised as follows: In Section 2, we consider the effect of the presence of each type of rigidity on the wage-growth distribution and in Section 3 we present more details on the data and sources. The methodology used and the results obtained are described in Section 4. Concluding observations appear in Section 5.

2 Downward Wage Rigidity and Wage Growth Distributions

It is well known that the presence of DNWR introduces a certain type of distortion to the shape of the actual (nominal) wage growth distribution. In particular, it shifts the probability mass from values of the support of the distribution that are below zero towards zero. This shift usually results in the collection of a non-zero-measure of probability mass at zero, which visually appears as a spike at that value in histogram plots of the actual wage-growth data.

[3] We do not investigate the simultaneous presence of menu costs as they were found to be of limited applicability in Christofides and Leung(2003).

Formally we can express this result as follows

$$DNWR: \begin{cases} F^n(\dot{w}) = F^N(\dot{w}) & \text{, if } \dot{w} > 0 \\ F^n(\dot{w}) = F^N(\dot{w}) \text{ and } \Pr\left(\dot{W}_i^n = \dot{w}\right) \geq 0 & \text{, if } \dot{w} = 0 \\ F^n(\dot{w}) = G^n\left(F^N(\dot{w})\right) \leq F^N(\dot{w}) & \text{, if } \dot{w} < 0 \end{cases} \tag{1}$$

where $F^N(\dot{w})$ is the cumulative distribution function (cdf) of the rigidity-free (or notional) nominal wage-growth distribution, $F^n(\dot{w})$ the cdf in the presence DNWR, $\Pr\left(\dot{W}_i^n = \dot{w}\right)$ the probability the DNWR-contaminated nominal wage growth $\left(\dot{W}_i^n\right)$ being equal to $\dot{w}$, and $G^n(\cdot)$ a functional that is used here generically to represent the type of distortions introduced by the presence of this type of rigidity.[4] The nature of the effect is visualised in the leftmost graph of the top row of Figure 1, where the light-shaded bars belong to the notional probability histogram, and the dark-shaded bars to the rigidity-contaminated probability histogram, in this case by DNWR.

The crucial difference between the cases of DNWR and DRWR that differentiates their effect on the shape of the actual wage-growth distribution from each other's, is that in the former case the relevant rigidity bound is the same for all bargaining units, i.e. the point zero, whereas in the latter the relevant rigidity bound, i.e. the expectation of price inflation during the contract period shared by the employer and the union, is likely to be different across the bargaining units in the population. In other words, in the case of DRWR there is a *distribution* of rigidity bounds across the population members, whereas in the case of DNWR there is a single rigidity bound that is common to all.

In order to examine the nature of the effect due to DRWR, we start-off with the relationship between the rigidity-contaminated and rigidity-free nominal wage growth for a particular

[4]Note that $G^n(F^N(\dot{w})) = F^N(\dot{w})$ for $\dot{w} \geq 0$.

contract (associated with a particular bargaining pair) indexed by i:

$$\dot{W}_i^r = \begin{cases} \dot{W}_i^N & , \text{if } \dot{W}_i^N \geq \dot{P}_i^e \\ \dot{\omega} \in [\dot{W}_i^N, \dot{P}_i^e] & , \text{if } \dot{W}_i^N < \dot{P}_i^e \end{cases} \tag{2}$$

where $\dot{W}_i^r$ is the rigidity-contaminated nominal wage growth due to DRWR, $\dot{W}_i^N$ the rigidity-free (or notional) nominal wage growth, and $\dot{P}_i^e$ the expected inflation that is relevant for the bargaining unit. This states that, if in the absence of DRWR the nominal wage growth would have been below the inflation expectation shared by the bargaining pair so that there would be a fall in real wage, in the presence of DRWR the nominal wage growth will typically take a higher value which can be up to the point where the real wage remains unaffected. At the same time, the presence of DRWR has no effect when the growth of the notional wage is above the expected inflation level.

At the population level it is clear that in the presence of DRWR there will be higher nominal wage growth for some contracts, i.e. those that were affected by the presence of DRWR, compared to the case of the absence of DRWR. As a result, there will be a shift of probability mass in the wage growth distribution to the right, towards the values of expected inflation in the population, *relative* to the case of no DRWR. Without making any additional assumptions about the nature of this shift, we can write the following in terms of the cdf's of the notional and rigidity-contaminated distributions

$$DRWR: \begin{cases} F^r(\dot{w}) = F^N(\dot{w}) & , \text{if } \dot{w} \geq \max\left(\dot{P}_i^e\right) \\ F^r(\dot{w}) = G^r\left(F^N(\dot{w})\right) \leq F^N(\dot{w}) & , \text{if } \dot{w} < \max\left(\dot{P}_i^e\right) \end{cases} \tag{3}$$

where $F^r(\dot{w})$ is the cdf of the nominal wage-growth distribution in the presence of DRWR, $F^N(\dot{w})$ is defined as before, and $G^r(\cdot)$ is a functional that is used generically to represent the type of distortions introduced by the presence DRWR.[5]

[5]Note that $G^r(F^N(\dot{w})) = F^N(\dot{w})$ for $\dot{w} \geq \max(\dot{P}_i^e)$.

The comparison of expressions (1) and (3) reveals the differences in the nature of the effects of the two types of rigidity. Firstly, in the presence of DRWR, the distortion in the shape of the distribution due to the shift of probability mass to the right can extend up to max $\left(\dot{P}_i^e\right)$, which is typically greater than zero, whereas in the case of DNWR the distortion extends only up to zero. One implication of this is that when the notional distribution is symmetric then, in the presence of DRWR, the actual distribution will be skewed to the right and the skewness will extend beyond zero[6]. The nature of the effect of DRWR is visualised in the rightmost graph of the top row of Figure 1 where, as before, the light-shaded bars belong to the notional probability histogram, the dark-shaded bars to the rigidity-contaminated probability histogram - in this case by DRWR - and the solid line represents the probability density function (pdf) of the distribution of expected inflation among bargaining pairs.

Secondly, if (as seems likely) the values of expected inflation are continuously distributed across the population members, the presence of DRWR cannot result in a concentration of non-zero-measure probability mass at any one of these values. Consequently, the presence of DRWR cannot be visually manifested by discontinuities (spikes), as is the presence of DNWR.

Thirdly, if we accept that typically the distribution of inflation expectations 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 DRWR.[7] This is different from the case of DNWR where the extent of nominal wage cuts diminishes as the magnitude of DNWR increases, and there are no nominal wage cuts when there is absolute DNWR. The case of absolute DRWR is visualised in the leftmost graph of the bottom row of

[6]McLaughlin(1999) in a paper that investigates the presence of DNWR alone, finds evidence of skewness that extends beyond zero. This is consistent with the presence of DRWR.

[7]The only case not to is when there is absolute DRWR and perfect foresight. Then, the distribution of expected inflation across bargaining pairs is degenerate at the actual inflation level and we would observe a spike at the realised inflation level.

Figure 1 where it is clear that, as long as the realised value of inflation is above the lowest value of expected inflation in the population, there will be real wage cuts.

From all the above we conclude that it is visually impossible to detect the presence of DRWR just by looking at the shape of the actual wage-growth distribution without having additional knowledge about the shape of the notional distribution.[8]

When some collective agreements are affected by DNWR and others by DRWR, then both types of distortions will be present in the shape of the actual wage-growth distribution. This is depicted in the rightmost graph of the bottom row of Figure 1 where there is both a spike at the bin containing the point zero and deficit in probability mass for bins to the left as well as to the right of that bin. Note that the two types of distortions have similar effect at the bins below zero, i.e. they reduce the probability mass concentrated there. On the other hand, they have opposite effects at the bin containing zero, since the presence of DRWR shifts mass from that bin to other bins to its right (negative effect), while the presence of DNWR shifts mass to that bin from bins to its left (positive effect). The nature of the combined effect will depend on the proportion of agreements affected by each type of rigidity, as well as the intensity of each type. Moreover, there is probability surplus for the bins that lie towards the right tail of the distribution of expected inflation and no effect to the bins that lie beyond $\max\left(\dot{P}_i^e\right)$.

3 Data and Sources

The contract data used in this paper are compiled by HRDC, the federal ministry responsible for monitoring agreements between firms and unions. The data base[9] contains information on provisions for 10,945 wage contracts signed in the Canadian unionised sector and involves

[8]In the case of DNWR, the assumption of continuity is sufficient to identify its effects due to the presence of a spike at zero, and the sudden fall in the level of the actual pdf to the left relative to its level to the right of zero.

[9]See Christofides and Stengos(2003) for a detailed description.

settlement dates as early as 1976 and as late as 1999. The agreements cover bargaining units involving 200 to nearly 80,000 employees, in both 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 that is used for the empirical analysis contains one observation for each contract, which is allocated to the year the contract became effective. Also, the wage change associated with each contract is defined over the whole of the life of the contract at *annual* rates.

Table 1 shows, for each year,[10] the number of contracts, the corresponding average of the non-contingent wage adjustment (WNC), and the total wage adjustment ($WNC + COLA$) over the life of the contracts (at annual rates). Also, the annual rate of Consumer Price Index inflation (CPI) and an estimate of expected inflation ($\widehat{\dot{P}^e}$).[11] From column 5 of this table one can see that the observation period can be divided into three consecutive periods relative to the level of inflation: 1977-1983 could be considered as a high inflation period, with average inflation at 9.58%, 1984-1992 a medium inflation period, with average inflation at 4.67%, and 1993-1997 a low inflation period, with average inflation at 1.46%. The comparison of the wage-growth figures in columns 3 (or 4) with those in column 5 reveals that there exists a positive relationship between the level of realised inflation and the *location* of the wage-growth distribution across years. Furthermore, there appears to be a positive relationship between the level of realised inflation and the *spread* of the wage-growth distribution, which can be seen from the box-plots of the data on total wage adjustment ($WNC + COLA$).

Table 2 shows the incidence of nominal wage adjustments relative to the value of zero and the realised level of inflation, by year. Only 102 (or 0.9%) of the contracts in the entire observation

[10]Because of the smaller number of contracts, the first two and the last three years in the sample are considered together in everything that follows.

[11]The proxy for expected inflation is constructed from an AR(6) regression model with a GARCH(1,1) error process.

period show nominal wage cuts, while a substantial number (1142 or 10.4%) show a wage freeze; jointly both figures could be considered as strong evidence in favour of the presence 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 wage freeze was above 35%, peaking at 51.0% in 1993. On the other hand, 6045 (or 55.2%) of the contracts exhibit - *ex ante* - negative real wage growth, while 4801 of them had at the same time positive nominal wage growth. As expected, the number of contracts that had exactly zero real wage growth is negligible, just 1 in this case, and the remaining 4899 (or 44.8%) contracts showed both nominal and real wage increase.

4 Empirical Analysis

4.1 Testing framework

The problem of testing for the presence of a particular type of rigidity using micro data could be stated as one where, having several yearly samples of observations on nominal wage growth

$$\mathcal{W} = \{\dot{w}_{ti}\}_{\substack{t=1,\ldots,T \\ i=1,\ldots,n_t}} \tag{4}$$

where $\dot{w}_{ti}$ represents the nominal wage growth agreed by the i'th bargaining unit for year t, one would want to test whether these were generated from rigidity-free or rigidity-contaminated yearly distributions. Formally, the hypotheses to be tested could be stated as follows

$$\begin{aligned} H_0 &: \quad F_t(\dot{w}) = F_t^N(\dot{w}) \\ H_1 &: \quad F_t(\dot{w}) = G^R\left(F_t^N(\dot{w})\right) \end{aligned} \tag{5}$$

where $F_t(\dot{w})$ is the cdf of the actual wage-growth distribution, $F_t^N(\dot{w})$ - as before - the cdf of the rigidity-free (or notional) wage-growth distribution, and $G^R\left(F_t^N(\dot{w})\right)$ the cdf of the rigidity-contaminated wage-growth distribution, in year t. The functional $G^R(\cdot)$ is used generically to represent the distortions introduced by the presence of rigidity, which can be either DNWR ($R = n$), or DRWR ($R = r$), or both ($R = nr$).[12]

Exploiting the distinct nature of the distortions in the shape caused by the presence of each type of rigidity,[13] a test for the presence of rigidity of type R could be based on the comparison of the shape of the estimated actual wage-growth distribution with the shape of the notional distribution (the counterfactual): if there were statistically significant differences in their shape of similar nature to those one would expect to find if rigidity of type R were present, this could be considered as evidence in favour of the presence of rigidity of type R.[14] Formally, this would require one to have information on both $F^N(\cdot)$, that describes the counterfactual distribution, and $G^R(\cdot)$, that characterises the differences due to the presence of rigidity. Obtaining information on the nature of $G^R(\cdot)$ is relatively straightforward, as we have already done, albeit informally, in Section 2. On the other hand, obtaining information on the nature of $F^N(\cdot)$ is not as easy. For one, we do not typically observe the notional wage growth, thus we cannot estimate it *directly* using such data. The way we could proceed is either to resort to economic theory for information, or infer information about it *indirectly* using the available actual wage-growth data.

The way we propose to proceed here follows the latter approach of using the actual wage-growth data to estimate jointly the notional distribution and the distortions due to the presence of both DNWR and DRWR. The basic idea is to test the hypotheses about the shape of the actual wage-growth distribution in terms of the heights of the bars of the corresponding prob-

[12]In this setup, we ignore the presence of measurement error in the wage growth data. This is a realistic assumption when we work with the Canadian contract data which are collected by the regulating agency HRDC.

[13]As we have seen in Section 2, the distortions associated with each type of rigidity are not, in general, observationally equivalent.

[14]This is usually the principle that underlies the various approaches for the testing for the presence of downward rigidity using micro data.

ability histogram. This approach can be seen as both a formalisation and an extension of the Kahn(1997) methodology. Its implementation can be organised in two stages:

Stage 1: Formulation of hypotheses in terms of the parameters of the probability histograms The aim in this stage is to transform the original problem of testing hypotheses about the cdf of the distribution of the actual wage-growth data from each year in the observation period, as described in (5), to one where we test equivalent hypotheses about the corresponding probability histogram. To achieve this, we first define these probability histograms, then parameterise the height of their bars, i.e. express the heights as functions of a set of variables, and, finally, construct hypotheses about the parameters of these functions that are equivalent to the original hypotheses stated in (5).

Specifically, let $P_{jt} \equiv F_t(h_{j+1,t}) - F_t(h_{j,t})$ be the height of the bar of the probability histogram of the actual wage-growth distribution in year t that corresponds to the j'th bin, denoted by $\mathcal{B}_{jt} \equiv [h_{j,t}, h_{j+1,t}]$, where the bin index $j \in \{-J, \ldots, 0, \ldots, J\}$ indicates the position of the bins in the probability histogram.[15] Given that our analysis aims to examine the shape of the distributions but not their location, j is defined to indicate the position of the bins relative to each other rather than relative to values on the real line. In particular, the bin indexed by $j = 0$ contains the median of the 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. We refer to the probability histograms defined in this way as 'standardised'.

Having defined the probability histograms in this particular way, the next step is to parameterise P_{jt} under the two hypotheses, i.e.

$$P_{jt} = \begin{cases} p^N\left(z^N_{jt}; b^N_j\right) & \text{, if } H_0 \text{ is true} \\ \\ p^R\left(z^R_{jt}; b^R_j\right) & \text{, if } H_1 \text{ is true} \end{cases} \tag{6}$$

[15] Then, the collection of the $2J + 1$ bars defines the probability histogram for that year.

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 variables that indicate the relative position of bin j in the probability histogram,[16] 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.[17]

In order to formulate hypotheses about the shape of the actual wage-growth distributions, we note that this is reflected by the height of the bars of the corresponding probability histograms. Furthermore, that, given the value of the observables, the height of the bars is determined by the value of the parameters of the functions that describe it. Therefore, in principle, hypotheses about the shape of the actual wage-growth distribution could be formulated in terms of the values of these parameters. In particular, suppose that there is a set of restrictions on b_j^R, namely $H\left(b_j^R\right) = 0$, such that[18]

$$H\left(b_j^R\right) = 0 \quad \Leftrightarrow \quad p^R\left(z_{jt}^R; b_j^R\right) = p^N\left(z_{jt}^N; b_j^N\right) \tag{7}$$

Then the proposed strategy to test for the presence of rigidity of type R is, firstly, to estimate

[16] Therefore, these variables will be functions of j.

[17] Therefore, 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 expected inflation values, i.e. the rigidity bounds for DRWR.

[18] It is natural to think of $G^R(F_t^N(\cdot))$ as the unrestricted case of $F_t(\cdot)$, and consequently, of $p^R(z_{jt}^R; b_j^R)$ as the unrestricted model of P_{jt}.

the parameter vector b_j^R, and subsequently to test the hypotheses

$$\begin{aligned} H_0: \quad & H\left(b_j^R\right) = 0 \\ H_1: \quad & H\left(b_j^R\right) \neq 0 \end{aligned} \tag{8}$$

Stage 2: Estimation of the probability histogram parameters and hypothesis testing

In this stage we estimate b_j^R and test the hypotheses stated in (8). The estimation is done in two steps, and exploits the fact that we have multiple samples on actual wage-growth.

In the first step, using the actual wage-growth data from each year in the observation period, we produce estimates of the heights of the bars of the corresponding probability histograms

$$\{\dot{w}_{ti}\}_{i=1,\ldots,n_t} \xrightarrow{\hat{P}_{jt}} \hat{p}_{jt} \quad , \qquad \text{for } j = -J, \ldots, J\,,\ t = 1, \ldots, T \tag{9}$$

where $\hat{P}_{jt}$ is an estimator of P_{jt} and $\hat{p}_{jt}$ the corresponding estimate. In the second step, using the set of T estimates of the height of the j'th bar, i.e. $\{\hat{p}_{jt}\}_{t=1,\ldots,T}$, as the set of 'observations' on $\hat{P}_{jt}$,[19] 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 $p^R\left(z_{jt}^R; b_j^R\right)$, and the regression equation will look like this

$$\hat{P}_{jt} \quad = \quad E\left(\hat{P}_{jt} \mid z_{jt}^R\right) + \varepsilon_{jt} \quad = \quad p^R\left(z_{jt}^R; b_j^R\right) + \varepsilon_{jt} \tag{10}$$

Therefore, by estimating this equation we get estimates of the parameter vector b_j^R and of its variance-covariance matrix, and we are thus able to test the restrictions stated in (8). More generally, one could use the entire set of height estimates to estimate jointly the regression equations of the $2J+1$ probability bar heights when this is more efficient.[20]

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

[20] This is discussed further in a subsequent section.

4.2 Parameterisation of probability histograms

Our chosen parameterisation for the heights of the bars of the notional probability histograms is the following

$$\begin{aligned} p^N\left(z_{jt}^N; b_j^N\right) &= \beta_{1|j|} + \beta_{2|j|} \times up_{jt} + \left(\beta_{3|j|} + \beta_{4|j|} \times up_{jt}\right) \times m_t \quad , \quad j \neq 0 \\ &= \beta_{10} + \beta_{30} \times m_t \quad , \quad j = 0 \end{aligned} \tag{11}$$

where m_t denotes the median of the actual wage-growth data in year t, and up_{jt} is a dummy variable that is equal to one if bin $\mathcal{B}_{jt}$ lies to the right of the bin containing the median ($j > 0$). 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, and, in particular, 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 symmetric around the bin containing m_t and, further, that its spread increases as its centre moves to higher values.[21] 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.[22]

In order to test for the presence of both types of rigidity, the parameterisation of the prob-

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

[22]The assumption in the original Kahn 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.

ability histogram under the alternative hypothesis should reflect the distortions due to the presence of both. We can always write

$$p^R\left(z_{jt}^R; b_j^R\right) = p^N\left(z_{jt}^N; b_j^N\right) + D^n\left(z_{jt}^n; \gamma\right) + D^r\left(z_{jt}^r; \delta\right) \text{ , for } R = nr \tag{12}$$

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 adopt simple, linear, parameterisations for both types of distortions. Our aim for the chosen parameterisation is to allow for a probability deficit for the bins below zero and a probability surplus for the bin containing zero, due to DNWR, and a shift in probability mass towards the bins that contain values of expected inflation, due to DRWR.

For the effect of DNWR we write

$$D^n\left(z_{jt}^n; \gamma\right) = \left(\gamma_1 + \gamma_2 \times m_t\right) \times d0_{jt} + \left(\gamma_3 + \gamma_4 \times m_t\right) \times dn_{jt} \tag{13}$$

where $d0_{jt}$ is a dummy variable that is equal to 1 if bin $\mathcal{B}_{jt}$ contains the point zero, and dn_{jt} a dummy variable that is equal to 1 if bin $\mathcal{B}_{jt}$ is to the left of the bin containing the point zero. Therefore, we allow for excess mass at zero and a deficit for the bins below zero that are linear functions of the location of the notional distribution, which we proxy by m_t.

To capture the effect of DRWR we write

$$D^r\left(z_{jt}^r; \delta\right) = \sum_k \delta_k \times dp_{k,jt} \tag{14}$$

where $dp_{k,jt}$ are dummy variables indicating the position of bin $\mathcal{B}_{jt}$ relative to the position of the bin containing the centre of the expected inflation distribution in year t,

$$dp_{k,jt} = \begin{cases} 1 & \text{if } j - J_t^P = k \\ 0 & \text{otherwise} \end{cases} \tag{15}$$

where J_t^P is the value of the index of the bin in year t that contains the centre of the expected inflation distribution in that year. For the empirical application we proxy this value either with the realised inflation in year t, measured by CPI_t, or a GARCH estimate of expected inflation $\left(\widehat{\dot{P}_t^e}\right)$.[23] The values taken by k are determined empirically.

With the above parameterisation one can see that to test for the absence of any type of rigidity we would have to test the null $H_0 : \gamma = 0 \ \cap \ \delta = 0$ against the alternative $H_1 : \gamma \neq 0 \ \cup \ \delta \neq 0$, where the null in this case represents the case where the actual wage-growth distribution coincides with the notional distribution. We could also test separately for the absence of either type of rigidity; in order to test for the absence of DRWR the relevant null hypothesis is $H_0 : \delta = 0$ against the alternative $H_1 : \delta \neq 0$, while for the absence of DNWR the relevant null hypothesis is $H_0 : \gamma = 0$ against the alternative $H_1 : \gamma \neq 0$. The rejection of the null in any of these cases would only indicate that the shape of the actual wage-growth distribution is different from the shape of the notional distribution in those parts that one would expect to find differences if the particular type of rigidity were present. In order to decide whether there is evidence in support of the presence of the particular type of rigidity, we would have to test in addition whether the nature of these differences is consistent with the presence of the particular type of rigidity, by testing individual hypotheses about the sign of the parameters. For example, for the case of DNWR we would have to test whether γ_1 is positive, and γ_2 and γ_3 negative.[24]

4.3 Estimation

In order to produce the estimates of the heights of the bars of the probability histograms ($\hat{p}_{jt}$), we use the proportion of observations in the sample for year t that fall in bin j as the estimator

[23] See Table 1 for their values.

[24] Any value of γ_4 is consistent with the presence of DNWR.

of P_{jt}.[25] This estimator, denoted by $\hat{P}_{jt}$, could be defined as

$$\hat{P}_{jt} \equiv \sum_{i=1}^{n_t} \frac{d_{jti}}{n_t} \tag{16}$$

where d_{jti} is a dummy variable that takes the value of 1 if $\dot{w}_{ti}$ falls in bin $\mathcal{B}_{jt}$ and 0 otherwise, and n_t is the number of observations in year t. Since $\Pr(d_{jti} = 1) = \Pr(\dot{w}_{ti} \in \mathcal{B}_{jt}) = P_{jt}$, then d_{jti} is a Bernoulli random variable with mean P_{jt}:

$$d_{jti} \sim Bernoulli(P_{jt}) \tag{17}$$

Furthermore, assuming that $\dot{w}_{ti} \overset{iid}{\sim} F_t(\dot{w})$, $\hat{P}_{jt}$ is the sample mean of i.i.d. $Bernoulli(P_{jt})$ random variables, and is thus an unbiased estimator of the true height P_{jt}, as well as consistent and asymptotically normal.

For the estimation of the unknown parameters, the $2J+1$ equations are treated as a system. After imposing the cross-equation parameter restrictions implied by the parameterisation of (12),[26] the equation for a typical observation for the stacked data can be written as follows

$$\hat{P}_{jt} = \sum_{q=-J}^{J} p^N\left(z_{qt}^N; b_q^N\right) \times d_{qt}^* + D^n\left(z_{jt}^n; \gamma\right) + D^r\left(z_{jt}^r; \delta\right) + \varepsilon_{jt} \tag{18}$$

where d_{qt}^* is a dummy variable defined as

$$d_{qt}^* = \begin{cases} 1 & \text{if } q = j \\ 0 & \text{otherwise} \end{cases} \tag{19}$$

[25] We use the median of the actual wage-growth data from year t, denoted by $\hat{m}_t$, as an estimate of m_t. Therefore the bin of the estimated probability histogram indexed by $j = 0$ is the one that contains $\hat{m}_t$. The bin width is set to be equal to 1% and the bin endpoints to take values from the set $\{\ldots, -1.5, -0.5, 0.5, 1.5, \ldots\}$. In this way, the point zero is at the centre of the bin that contains it, and so, small wage changes around zero also fall in the same bin. Furthermore J is chosen to be equal to 8, thus each probability histogram consists of 17 bins that cover in total an interval of 17 percentage points. In this way we achieve the coverage of more than 97% of the data points in each yearly sample.

[26] Specifically, the parameter vectors that capture the effect of the rigidities, i.e. γ and δ, are common to all equations.

In matrix form we can write

$$\hat{\mathbf{P}} = \mathbf{Z}\mathbf{b} + \varepsilon \tag{20}$$

where $\hat{\mathbf{P}} \equiv \begin{bmatrix} \hat{\mathbf{P}}_{-J} & \hat{\mathbf{P}}_{-J+1} & \cdots & \hat{\mathbf{P}}_0 & \cdots & \hat{\mathbf{P}}_{J-1} & \hat{\mathbf{P}}_J \end{bmatrix}'$ is the vector of dependent variables for the entire system, and $\hat{\mathbf{P}}_j \equiv \begin{bmatrix} \hat{P}_{j1} & \hat{P}_{j2} & \cdots & \hat{P}_{jT} \end{bmatrix}$ the vector of dependent variables that corresponds to equation j.

The choice of optimal estimation method for the parameters of the system depends on the nature of the variance-covariance matrix of the vector $\hat{\mathbf{P}}$ of estimators, denoted by $Var\left(\hat{\mathbf{P}}\right)$. Using (16), the typical element of this matrix can be written as

$$\begin{aligned} Cov\left(\hat{P}_{jt}, \hat{P}_{\zeta\tau}\right) &= Cov\left(\sum_{i\in\mathcal{I}_t} \frac{d_{jti}}{n_t}, \sum_{\iota\in\mathcal{I}_\tau} \frac{d_{\zeta\tau\iota}}{n_\tau}\right) \\ &= \sum_{i\in\mathcal{I}_t\cap\mathcal{I}_\tau} \frac{Cov\left(d_{jti}, d_{\zeta\tau i}\right)}{n_t n_\tau} + \sum_{i\in\mathcal{I}_t} \sum_{\substack{\iota\in\mathcal{I}_\tau \\ \iota\neq i}} \frac{Cov\left(d_{jti}, d_{\zeta\tau\iota}\right)}{n_t n_\tau} \end{aligned} \tag{21}$$

where $\mathcal{I}_t$ and $\mathcal{I}_\tau$ are the sets of indices denoting the bargaining pairs which appear in our sample to have a contract agreement in years t and τ respectively, while $j, \zeta \in \{-J, \ldots, J\}$ and $t, \tau \in \{1, \ldots, T\}$. Treating the wage growth associated with different bargaining pairs as being independent across time, the second sum in the above expression is equal to zero. Furthermore, using (17), we can write

$$\begin{aligned} Cov\left(d_{jti}, d_{\zeta\tau i}\right) &= Ed_{jti}d_{\zeta\tau i} - Ed_{jti}Ed_{\zeta\tau i} \\ &= \Pr\left(d_{jti} = d_{\zeta\tau i} = 1\right) - \Pr\left(d_{jti} = 1\right)\Pr\left(d_{\zeta\tau i} = 1\right) \\ &= \Pr\left(d_{jti} = d_{\zeta\tau i} = 1\right) - P_{jt}P_{\zeta\tau} \end{aligned} \tag{22}$$

and therefore (21) can be re-written as[27]

$$Cov\left(\hat{P}_{jt}, \hat{P}_{\zeta\tau}\right) = \begin{cases} \frac{P_{jt}(1-P_{jt})}{n_t} & , t = \tau \text{ and } j = \zeta \\ -\frac{P_{jt}P_{\zeta t}}{n_t} & , t = \tau \text{ and } j \neq \zeta \\ \sum_{i\in\mathcal{I}_t\cap\mathcal{I}_\tau} \frac{\Pr\left(d_{jti}=d_{\zeta\tau i}=1\right) - P_{jt}P_{\zeta\tau}}{n_t n_\tau} & , t \neq \tau \end{cases} \tag{23}$$

[27]Using that, for $t = \tau$, the quantity $\Pr\left(d_{jti} = d_{\zeta\tau i} = 1\right)$ is equal to P_{jt} if $j = \zeta$, and equal to 0 otherwise.

Clearly $Var\left(\hat{\mathbf{P}}\right)$ is not spherical, and therefore the Ordinary Least Squares (OLS) procedure, despite producing consistent estimates of $\mathbf{b}$, gives wrong standard error estimates. Therefore we opt for the Feasible Generalised Least Squares (FGLS) procedure, substituting the probabilities in the right-hand side of (23) with consistent estimates; in the case of the probabilities of the form P_{jt} with the estimates obtained in stage 2 (i.e. $\hat{p}_{jt}$), and for $\Pr(d_{jti} = d_{\zeta\tau i} = 1)$ with estimates produced in a similar way

$$\Pr\left(\widehat{d_{jti} = d_{\zeta\tau i}} = 1\right) = \sum_{i \in \mathcal{I}_t \cap \mathcal{I}_\tau} \frac{d_{jti} d_{\zeta\tau i}}{\#\left(\mathcal{I}_t \cap \mathcal{I}_\tau\right)} \xrightarrow{p} \Pr\left(d_{jti} = d_{\zeta\tau i} = 1\right) \tag{24}$$

where $\#\left(\mathcal{I}_t \cap \mathcal{I}_\tau\right)$ is the number of elements in the set $\mathcal{I}_t \cap \mathcal{I}_\tau$.[28]

4.4 Results

In Table 3 we present the estimation results when we apply the FGLS estimator (columns 2 and 3), and the OLS estimator with corrected (columns 4 and 5) and uncorrected standard errors (columns 6 and 7). To obtain these results we have used the GARCH approach to estimate the expected inflation rate.[29] The table is divided in three panels; the top panel includes the estimates associated with the notional distribution (β's), the middle panel those associated with the distortion due to the presence of DNWR (γ's), and the bottom panel those associated with the distortion due to the presence of DRWR (δ's). Furthermore in Table 4 we present the results from testing joint hypotheses about the parameters of the model using the Wald and F statistics, which are based on the results from the FGLS estimation. Next we discuss the results from the FGLS estimation.[30]

[28] In order to obtain the results described in the next section, we have assumed - a priori - that all these quantities are equal to zero. Given that our expectation is that the corresponding estimates would have been relatively small and close to zero, we do not think that this assumption has affected considerably these results.

[29] When using the CPI approach we do not get as strong results as those we report here.

[30] The OLS results with corrected standard errors are, at least qualitatively, similar; they show a shift of probability mass to the right towards the values of expected inflation, a spike at zero, and mass deficit below

Firstly, from line 1 of Table 4, we see that we reject the null that the shape of the actual wage-growth distribution coincides with the shape of the rigidity-free distribution. We also reject the hypotheses of the absence of DRWR (line 2) and DNWR (line 3), when these are tested separately. This is hardly surprising given that the majority of the parameters that measure the distortion due to the presence of rigidities in Table 3 are statistically significant.

Looking more closely at the results that appear in the bottom panel of this table we see that the estimated excess probability mass (δ_0) attracted by the bin containing the GARCH estimate is 6.51%, and is statistically significant. As we move further to bins to its left, the respective estimate increases to 6.99% for the first bin and remains statistically significant, and then for the rest of the bins becomes much smaller in magnitude (below 0.5%), with its sign being positive for some bins and negative for others; these coefficients are not always statistically significant. On the other hand, as we move further to bins to its right, the respective estimates decrease but remain positive and statistically significant. This pattern reveals a shift of mass to the right which is similar with what we would expect if DRWR were present.

The estimates of the parameters measuring the effect due to the presence of DNWR (middle panel) are also significant and have signs that are consistent with the presence of this type of rigidity. When the distribution is centered at zero, the bin containing the zero attracts an estimated excess probability mass (γ_1) of 10.90%, that diminishes by 1.73% for each 1% increase in the median actual wage growth. Each bin that contains negative values of wage growth has a probability deficit of 2.08% that decreases as the median increases.

In line 4 of Table 4 we present the result from testing the hypothesis that the shape of the notional distribution remains the same as the centre of the distribution changes location, and we see that this is rejected. We also note from Table 3 that most of the $\beta_{4|j|}$ parameters are

zero. For the OLS results without correction of the standard errors we note that all of the parameters that measure the effect of DRWR, with the exception of one, are statistically insignificant.

statistically significant, which suggests that the change in the height of the bins to the right of bin zero is different from that of the bins to its left. Combining these two results we can reach the conclusion that the skewness of the notional distribution varies with its location.

We also reject the hypothesis that the probability histogram of the notional wage-growth distribution is symmetric around the bin containing the median of the actual wage-growth distribution (line 5, Table 4). If we believed that the median of the notional distribution were close enough to the median of the actual so that they were both located in the same bin, then we could interpret this result as one that suggests that the notional distribution is non-symmetric. However, given the result that there is a shift of mass to the right in the case of the actual relative to the notional distribution, we are cautious to accept this interpretation.

Because of the large number or estimated parameters and the presence of interaction terms, the importance of the estimated distortions due to the presence of both types of rigidity is not immediately clear. Therefore, in Figure 2, we draw the fitted probability histograms for the notional and actual wage-growth distributions, for representative years in the sample. The histograms in this figure are 'standardised', therefore the bin indexed by zero contains the median of the actual wage-growth data from the relevant year. The light-shaded bars correspond to the notional distribution, i.e. $p^N\left(z_{jt}^N;\hat{b}_j^N\right)$, while the dark-shaded bars to the actual distribution, i.e. $p^R\left(z_{jt}^R;\hat{b}_j^R\right)$. Clearly there is a shift of mass to the right that extends beyond zero, a feature that is consistent with the presence of DRWR. Furthermore, there is a spike at the bin containing the zero point, for example bin -5 in the graphs for years 1983 and 1989, bin -4 for

1984, and bin -2 for 1992.[31]

5 Conclusion

In this paper, we study collective bargaining wage outcomes drawn from the Canadian unionised sector, over a long period of diverse inflation experience. Earlier studies involving this data found evidence for the presence of DNWR. The challenge was to specify mechanisms consistent with the notion of DRWR and to superimpose these mechanisms on the broad approach used to measure DNWR in the past. The results obtained suggest that DRWR is clearly present in the data and that it can be identified over and above substantial DNWR effects.

[31]We have estimated several variations of the model in order to examine the sensitivity of our results to the particular specification of the model and found that these were robust, at least in a qualitative sense; in all cases we estimated a shift of mass to the right towards the point zero and the bins we expect to contain the values of expected inflation, the presence of excess mass at zero, and a mass deficit in the part of the distribution that lies below zero.

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Year	#	WNC	WNC+COLA	CPI	$\widehat{\dot{P}^e}$
1977	226	6.48	8.69	7.55	7.22
1978	673	7.12	8.16	8.01	8.42
1979	569	8.41	10.64	8.95	8.45
1980	520	11.15	12.39	9.13	9.28
1981	450	12.76	13.64	10.16	11.66
1982	562	9.85	10.31	12.43	10.43
1983	643	4.47	4.89	10.80	6.05
1984	676	3.45	3.76	5.86	4.50
1985	519	3.44	3.78	4.30	3.81
1986	551	3.44	3.65	3.96	4.08
1987	557	3.56	3.90	4.18	4.37
1988	556	4.61	4.92	4.34	3.97
1989	493	5.41	5.68	4.05	4.83
1990	547	5.43	5.79	4.99	4.55
1991	530	3.69	3.89	4.76	5.91
1992	632	2.11	2.16	5.62	1.49
1993	516	0.65	0.75	1.49	2.00
1994	471	0.51	0.60	1.86	0.50
1995	460	0.82	0.86	0.16	2.24
1996	448	1.14	1.22	2.16	1.43
1997	346	1.76	1.87	1.62	1.95
Total	10945				

Table 1: Descriptive statistics.

Year	$\dot{w} < 0$		$\dot{w} = 0$		$0 < \dot{w} < CPI$		$\dot{w} = CPI$		$\dot{w} > CPI$	
	#	%	#	%	#	%	#	%	#	%
1977			2	*0.9*	86	*38.1*			138	*61.1*
1978					393	*58.4*			280	*41.6*
1979					198	*34.8*			371	*65.2*
1980					43	*8.3*			477	*91.7*
1981			1	*0.2*	38	*8.4*			411	*91.3*
1982	1	*0.2*	3	*0.5*	397	*70.6*			161	*28.6*
1983	4	*0.6*	26	*4.0*	597	*92.8*			16	*2.5*
1984	1	*0.1*	61	*9.0*	559	*82.7*			55	*8.1*
1985	1	*0.2*	26	*5.0*	286	*55.1*			206	*39.7*
1986	2	*0.4*	24	*4.4*	238	*43.2*	1	*0.2*	286	*51.9*
1987			17	*3.1*	307	*55.1*			233	*41.8*
1988			4	*0.7*	203	*36.5*			349	*62.8*
1989					60	*12.2*			433	*87.8*
1990			14	*2.6*	136	*24.9*			397	*72.6*
1991	2	*0.4*	57	*10.8*	243	*45.8*			228	*43.0*
1992	7	*1.1*	82	*13.0*	488	*77.2*			55	*8.7*
1993	18	*3.5*	263	*51.0*	116	*22.5*			119	*23.1*
1994	53	*11.3*	186	*39.5*	146	*31.0*			86	*18.3*
1995	9	*2.0*	162	*35.2*	2	*0.4*			287	*62.4*
1996	3	*0.7*	164	*36.6*	174	*38.8*			107	*23.9*
1997	1	*0.3*	50	*14.5*	91	*26.3*			204	*59.0*
Total	102	*0.9*	1142	*10.4*	4801	*43.9*	1	*0.0*	4899	*44.8*

Table 2: Wage-growth statistics.

	FGLS		OLS-corrected		OLS	
Parameter	**Estimate**	**(Std. Err.)**	**Estimate**	**(Std. Err.)**	**Estimate**	**(Std. Err.)**
β_{10}	0.3285^{**}	(0.0081)	0.2869^{**}	(0.0094)	0.2869^{**}	(0.0193)
β_{11}	0.0574^{**}	(0.0035)	0.1774^{**}	(0.0071)	0.1774^{**}	(0.0196)
β_{12}	0.0253^{**}	(0.0022)	0.0788^{**}	(0.0053)	0.0788^{**}	(0.0201)
β_{13}	0.0291^{**}	(0.0025)	0.0700^{**}	(0.0041)	0.0700^{**}	(0.0201)
β_{14}	0.0251^{**}	(0.0019)	0.0553^{**}	(0.0036)	0.0553^{**}	(0.0204)
β_{15}	0.0199^{**}	(0.0021)	0.0518^{**}	(0.0033)	0.0518^{*}	(0.0206)
β_{16}	0.0000	(0.0051)	0.0536^{**}	(0.0030)	0.0536^{**}	(0.0194)
β_{17}	0.0243^{**}	(0.0024)	0.0547^{**}	(0.0030)	0.0547^{**}	(0.0181)
β_{18}	0.0251^{**}	(0.0021)	0.0550^{**}	(0.0028)	0.0550^{**}	(0.0172)
β_{21}	0.1785^{**}	(0.0082)	0.0221^{*}	(0.0108)	0.0221	(0.0194)
β_{22}	0.0311^{**}	(0.0058)	-0.0125	(0.0080)	-0.0125	(0.0223)
β_{23}	-0.0213^{**}	(0.0041)	-0.0359^{**}	(0.0061)	-0.0359	(0.0236)
β_{24}	-0.0297^{**}	(0.0027)	-0.0435^{**}	(0.0051)	$-0.0435^{\dagger}$	(0.0245)
β_{25}	-0.0243^{**}	(0.0028)	-0.0489^{**}	(0.0040)	-0.0489^{*}	(0.0246)
β_{26}	-0.0039	(0.0052)	-0.0555^{**}	(0.0034)	-0.0555^{*}	(0.0229)
β_{27}	-0.0215^{**}	(0.0025)	-0.0562^{**}	(0.0032)	-0.0562^{**}	(0.0216)
β_{28}	-0.0254^{**}	(0.0029)	-0.0560^{**}	(0.0029)	-0.0560^{**}	(0.0207)
β_{30}	-0.0197^{**}	(0.0010)	-0.0134^{**}	(0.0012)	-0.0134^{**}	(0.0021)
β_{31}	0.0074^{**}	(0.0007)	-0.0040^{**}	(0.0010)	$-0.0040^{\dagger}$	(0.0021)
β_{32}	0.0066^{**}	(0.0006)	0.0030^{**}	(0.0009)	0.0030	(0.0022)
β_{33}	0.0010^{*}	(0.0005)	-0.0013^{*}	(0.0006)	-0.0013	(0.0022)
β_{34}	-0.0017^{**}	(0.0003)	-0.0027^{**}	(0.0005)	-0.0027	(0.0023)
β_{35}	-0.0019^{**}	(0.0003)	-0.0020^{**}	(0.0004)	-0.0020	(0.0023)
β_{36}	0.0005	(0.0006)	-0.0029^{**}	(0.0004)	-0.0029	(0.0023)
β_{37}	-0.0017^{**}	(0.0003)	-0.0034^{**}	(0.0003)	-0.0034	(0.0023)
β_{38}	-0.0018^{**}	(0.0003)	-0.0034^{**}	(0.0003)	-0.0034	(0.0023)
β_{41}	-0.0174^{**}	(0.0013)	-0.0022	(0.0016)	-0.0022	(0.0028)
β_{42}	-0.0022^{*}	(0.0011)	0.0013	(0.0013)	0.0013	(0.0030)
β_{43}	0.0028^{**}	(0.0007)	0.0028^{**}	(0.0009)	0.0028	(0.0030)
β_{44}	0.0051^{**}	(0.0005)	0.0054^{**}	(0.0007)	$0.0054^{\dagger}$	(0.0031)
β_{45}	0.0041^{**}	(0.0004)	0.0043^{**}	(0.0006)	0.0043	(0.0031)
β_{46}	$0.0013^{\dagger}$	(0.0007)	0.0052^{**}	(0.0005)	$0.0052^{\dagger}$	(0.0030)
β_{47}	0.0020^{**}	(0.0003)	0.0049^{**}	(0.0004)	$0.0049^{\dagger}$	(0.0029)
β_{48}	0.0026^{**}	(0.0004)	0.0042^{**}	(0.0003)	0.0042	(0.0029)
γ_1	0.1090^{**}	(0.0051)	0.1813^{**}	(0.0106)	0.1813^{**}	(0.0167)
γ_2	-0.0173^{**}	(0.0010)	-0.0323^{**}	(0.0019)	-0.0323^{**}	(0.0037)
γ_3	-0.0208^{**}	(0.0011)	-0.0543^{**}	(0.0029)	-0.0543^{**}	(0.0124)
γ_4	0.0009^{**}	(0.0003)	0.0039^{**}	(0.0003)	$0.0039^{\dagger}$	(0.0022)
δ_{-7}	0.0033^{**}	(0.0011)	-0.0001	(0.0006)	-0.0001	(0.0110)
δ_{-6}	-0.0008	(0.0013)	-0.0040^{**}	(0.0009)	-0.0040	(0.0125)
δ_{-5}	0.0027^{*}	(0.0014)	-0.0095^{**}	(0.0014)	-0.0095	(0.0137)
δ_{-4}	-0.0025	(0.0015)	-0.0158^{**}	(0.0022)	-0.0158	(0.0146)
δ_{-3}	-0.0022	(0.0018)	-0.0192^{**}	(0.0028)	-0.0192	(0.0153)
δ_{-2}	0.0046^{*}	(0.0021)	-0.0168^{**}	(0.0036)	-0.0168	(0.0156)
δ_{-1}	0.0699^{**}	(0.0041)	0.0237^{**}	(0.0055)	0.0237	(0.0156)
δ_0	0.0651^{**}	(0.0052)	0.0351^{**}	(0.0058)	0.0351^{*}	(0.0154)
δ_1	0.0366^{**}	(0.0042)	0.0202^{**}	(0.0050)	0.0202	(0.0149)
δ_2	0.0238^{**}	(0.0030)	$0.0076^{\dagger}$	(0.0041)	0.0076	(0.0142)
δ_3	0.0073^{**}	(0.0019)	-0.0048	(0.0033)	-0.0048	(0.0131)
δ_4	0.0051^{**}	(0.0015)	-0.0056^{*}	(0.0026)	-0.0056	(0.0116)
δ_5	0.0067^{**}	(0.0013)	0.0005	(0.0019)	0.0005	(0.0100)

Significance levels : $\dagger$: 10% $*$: 5% $**$: 1%

Table 3: Estimation results.

#	W	$Pr(\chi^2_q > W)$	F	$Pr(F_{(q,n-k)} > F)$
1[a]	1312.8850	0	77.2285	0
2[b]	483.0889	0	37.1606	0
3[c]	744.6331	0	186.1583	0
4[d]	1026.1230	0	60.3602	0
5[e]	996.3245	0	62.2702	0

[a] $H_0 : \gamma = 0 \cap \delta = 0, H_1 : \gamma \neq 0 \cup \delta \neq 0 \quad (q = 17,\ n - k = 351)$
[b] $H_0 : \delta = 0, H_1 : \delta \neq 0 \quad (q = 13,\ n - k = 351)$
[c] $H_0 : \gamma = 0, H_1 : \gamma \neq 0 \quad (q = 4,\ n - k = 351)$
[d] $H_0 : \beta_{3|j|} = \beta_{4|j|} = 0, H_1 : \beta_{3|j|} \neq 0 \cup \beta_{4|j|} \neq 0,\ \forall j \quad (q = 17,\ n - k = 351)$
[e] $H_0 : \beta_{2|j|} = \beta_{4|j|} = 0, H_1 : \beta_{2|j|} \neq 0 \cup \beta_{4|j|} \neq 0,\ \forall j \quad (q = 16,\ n - k = 351)$

Table 4: Joint test results.

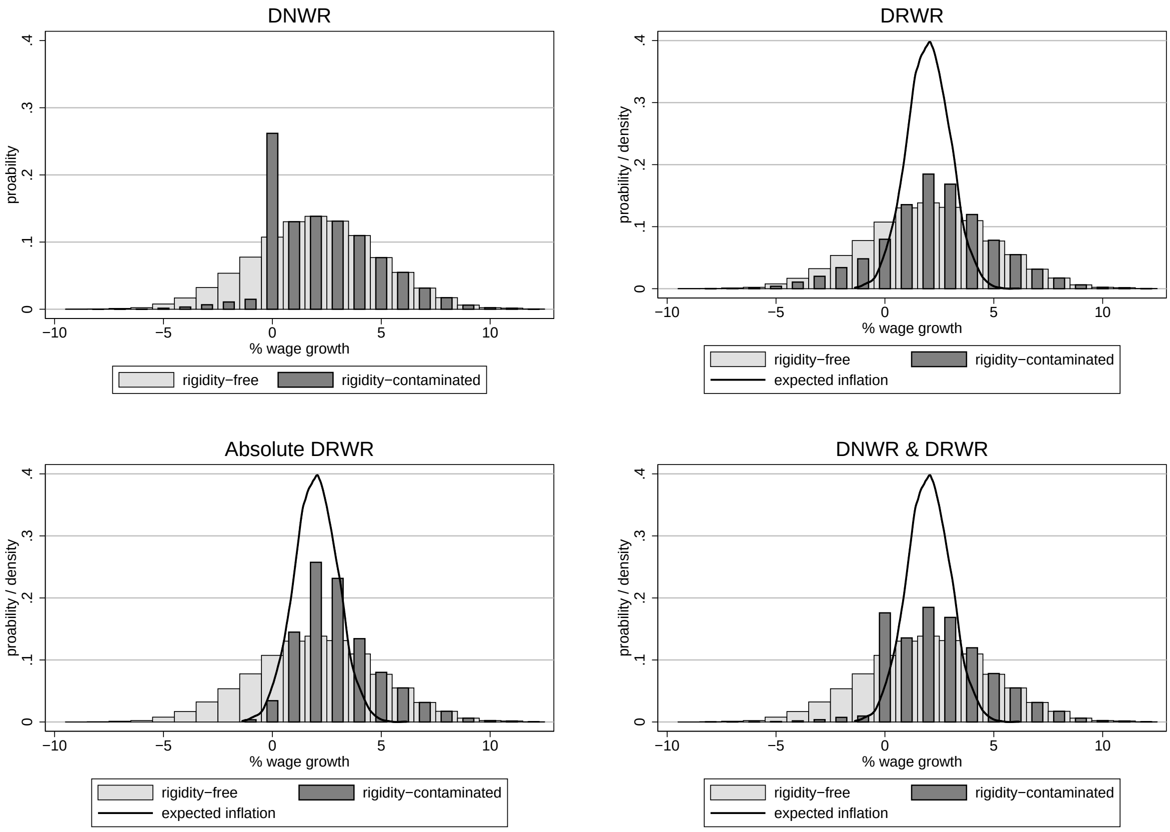

Figure 1: Shapes of simulated rigidity-free (notional) and rigidity-contaminated nominal wage-growth distributions.

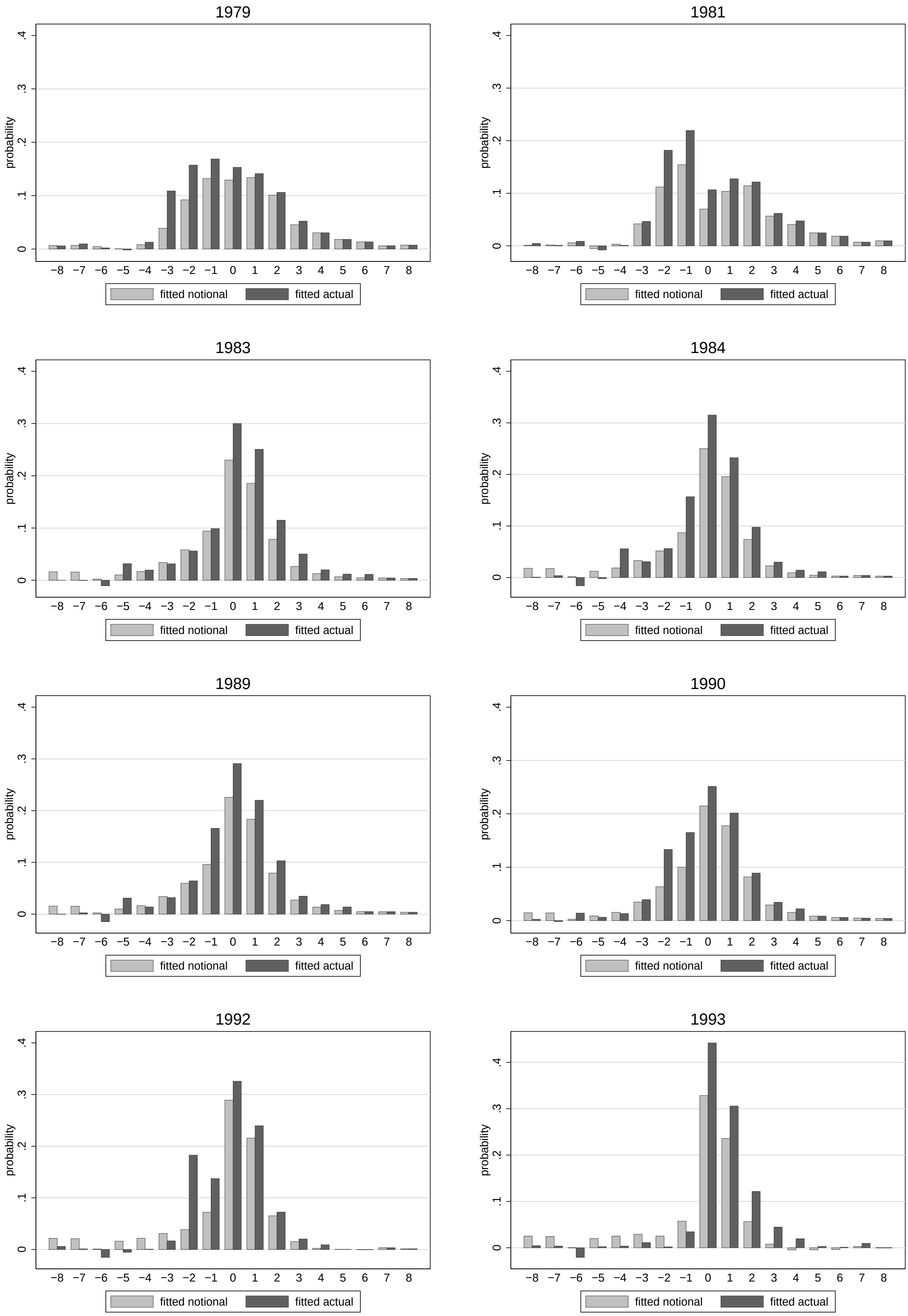

Figure 2: Notional Vs Actual nominal wage-growth distributions (fitted values).