Nominal wage rigidity in Brazil

Hyeon Jin Jeong*

Márcio Issao Nakane†

2022

Abstract

This study investigates nominal wage rigidities in the Brazilian formal labor market. It explores two features of nominal wage rigidity: first, the extent to which job stayers face wage freeze in their annual wage contracts; and, second, how sticky nominal wages are. Using RAIS administrative dataset for the period 2007-2016, we document that, annually, about 17.5% of job stayers are expected to experience wage freeze. The application of survival analysis techniques show that nominal rigidity display significant heterogeneities across geographical regions and income groups. The estimation of survival function indicates that the probability of a job stayer having wage freeze in each period is about 25.2%.

Keywords: nominal wage rigidity, nominal wage stickiness

Resumo

Este estudo investiga a rigidez nominal dos salários no mercado de trabalho formal brasileiro. Ele explora duas características da rigidez nominal dos salários: primeiro, até que ponto os que permanecem no emprego enfrentam congelamento de salários em seus contratos anuais de salário; e, segundo, quão rígidos são os salários nominais. Usando a base de dados administrativos da RAIS para o período 2007-2016, documentamos que, anualmente, cerca de 17,5% dos que permanecem no emprego devem sofrer congelamento salarial. A aplicação de técnicas de análise de sobrevivência mostra que a rigidez nominal apresenta heterogeneidades significativas entre regiões geográficas e grupos de renda. A estimação de uma função de sobrevivência indica que a probabilidade de um empregado ter seu salário congelado em cada período é de 25,2.%

Palavras chaves: rigidez de salário nominal, duração da rigidez salarial

Área 13 - Economia do Trabalho

Classificação JEL: J31, J41, J52

*Department of Economics, University of São Paulo. Financial support from CNPq is acknowledged.
†Department of Economics, University of São Paulo

1 Introduction

Wage rigidity has been pointed out as one of the factors that explain why nominal shocks can cause impact on real variables, such as unemployment and output. Despite its relevance to modern macroeconomics, there have been attempts to understand it only in relatively recent times. Regardless of the consensus on its existence in real world, the discussion on how to measure wage rigidity is still ongoing. Indeed, different empirical strategies are used to measure it. Consequently, there are often divergent reported results. Not only the lack of consensus on measurement makes it difficult to understand, compare and analyze results, but also there is another obstacle to overcome: mostly, studies have been conducted using self reported surveys, rather than administrative records; in this case measurement error can cause problems to the estimation.

Wage rigidity describes the situation in which it is not possible to adjust wage to the optimal level. Two characteristics can be used as signals to recognize it: a great number of observations around some certain point, for example, around 0 nominal wage variation, and the persistence of no wage change for several periods. The first feature is often observed when faced with the resistance to have wage cut, called downward nominal wage rigidity. The second feature is known as staggered wage setting or sticky wage setting.

This study investigates the existence of nominal wage rigidity and its extent in the Brazilian formal labor market. The study answers two related questions: first, we investigate how rigid nominal wage is for job stayers; second, we assess how sticky nominal wages are.

The first question is answered using RAIS, Brazilian administrative records on employees, reported by employers. We identify job stayers and separate them into 3 categories: hourly wage freeze, hourly wage cut and hourly wage increase. Then three different indicators are calculated in order to have an overview on the labor market. The share of each category is stable over the studied years, even under economic turbulence. Annually, about 17.5% of job stayers are expected to experience wage freeze. In Brazil, nominal wage cut requires a legal process to be implemented, so it ends up creating an extra barrier to employers. Due to all this difficulty to overcome, wage cuts are rare, experienced by about 3% of job stayers; however, they are observed in every year.

The second question concerns the stickiness of nominal wage. We employ survival analysis approach to address this question. Survival function for each year is estimated using KM survival estimator. As the main finding of this part, we found that employees in North and Northeast have the stickiest wage, while employees from South and Southeast have the least sticky wages. Heterogeneity across income groups is found as well: the higher is the wage, the stickier it is. As the final task of this part, the survival regression is estimated using Maximum Likelihood Estimator. The estimation results show that the heterogeneity across regions and income groups is significant at 1%.

The main contribution of this study is to provide empirical evidence of the nominal wage rigidity for Brazilian formal labor market. So this finding could be used in further studies which need a prior for the value of nominal wage rigidity.

2 Brief literature review

Most economists agree with the view that instant wage adjustment in response to any type of shocks is an unrealistic assumption. Most mainstream models point to the nominal price and wage rigidity as the cause to possible linkage between nominal shocks and impacts on real variables. This so called nominal wage rigidity is present in theoretical models; however, little is certain about what defines it or how to measure it or even the existence in the real world. Basically, there are two characteristics that identify the existence of nominal wage rigidity (NWR). Inspired by the idea of not being able to reduce wage to the equilibrium level, the first feature to describe NWR is the resistance to have wage cut. As a consequence, NWR would be recognized if there is a considerable number of workers who have wage frozen, i.e. zero wage change. The second feature that describes NWR is given by the time it takes to adjust nominal wages.

Based on the observation made by Fallick et al (2016), despite the concept being quite old, this theme has been explored only recently, mainly because inflation rate in the US was high enough to keep this problem far away from the reality. Indeed, as noted by Taylor et al. (2016), the introduction of rational expectation became a turning point for macroeconomists and since then the theme has been extensively investigated, developing several models that incorporate the idea, such as Calvo model of pricing, developed by Calvo (1983), to introduce a random duration of a contract.

There is relative consensus concerning the problem that NWR would cause to the economy, in the theoretical literature. So there have been many attempts to examine especially downward nominal wage rigidity (DNWR) using different empirical approaches (McLaughin, 1994; Dickens et al., 2007; Elsby, 2009, Bauer et al., 2003, Babecky et al., 2009). However, Goette et al. (2007) observed that there is not consensus on the extent of DNWR in the empirical literature, nor consensus on how to measure it, as noticed by Deelen et al. (2015). Also, other studies have looked for reasons for wage rigidity, by surveys and questionnaires responded by firms. Besides labor regulation, collective bargaining, union density, and many other labor related variables that affect decision to wage cut, as reported in Du Caju et al. (2014), employees' morale is found to be one of the relevant factors that employers consider, as Bewley (2004) reports. Fehr et al. (2005) has a similar finding: perception of fairness, employees' loyalty to the employer and work morale are relevant factors to NWR, refleting in different behavior regarding wage cuts between job stayers and job switchers.

As stated above, how to measure wage rigidity has become a very important issue in this branch of the literature. There have been numerous attempts to create an indicator that would lead to precise measurement. One of the first and the most intuitive indicator is the number of employees who experienced wage freeze, as used in McLaughin (1994). Dickens et al. (2007) proposes the ratio between the fraction of employees with wage freeze and the sum of the fraction of employees 'at risk': those who had wage cut and those who had wage freeze. Concerns on the reliability of the data have arisen as an important point to consider prior to analysis, as a variety of empirical studies used individual reports, as remarked by Elsby et al.(2019). So, as an attempt to correct measurement error, many works have used assumptions on errors in the theoretical wage change distribution. Deelen et al. (2015) finds that the assumptions on the wage change distribution under flexible wage setting may be the sources that result in different levels of wage rigidity, even when the same dataset is explored.

Regarding the Brazilian labor market, there have not been many attempts to explore this theme, possibly because during times of relatively high inflation rate, DNWR is not a relevant restriction, whereas wage indexation is a more complicated problem faced by policy makers. Messina et al (2014) explores how the reactions of employers and employees changed during the period of a speedy disinflation process. Using RAIS of Minas Gerais for the period of 1995-2002, they find that the employees in the state do not face DNWR, but wage indexation persists even after the disinflation, partly attributed by the high union density in Brazil. With the lack of empirical study that provides evidence for NWR in Brazilian labor market, some works end up using prior value for nominal wage rigidity of European or US labor market. [1]

3 Data

The main dataset used to study wage stickiness for the Brazilian labor market is the Brazilian annual administrative record regarding employer-employee relationship, Relação Anual de Informações Sociais (RAIS, Annual Report on Social Information). Collected by Ministério do Trabalho e Emprego (MTE, Ministry of Labor and Employment) it was created in the '70s to monitor the formal labor market, by gathering employers' annual update regarding their working staff.

[1] See Vasconcelos et al (2012), Carvalho et al (2011), Schumanski (2015).

This employer-employee matched dataset contains information on base wage, individual identification, contracted working hours per week, employee's characteristics, job features, firm characteristics, employer-employee relationship, employer's leaving during the base year, as of 31st December of each year. Since it is a huge database, only variables considered relevant to the analysis are extracted: municipality, separation date if applicable, admission date, contracted working hours, base wage, type of wage, PIS/Pasep (individual identification), CNPJ/CEI (firm identification), position, classification of economic activities. Also, RAIS shows not only the active staff at the base date, but in-year-separated employees' information is available as well. The procedure of filing is compulsory for all registered employers in Brazil with the possibility of penalties foreseen in law in case they do not meet the deadline, omit information or provide incorrect statements. Based on the estimation made by Instituto Brasileiro de Geografia e Estatística (IBGE, Brazilian Institute of Geography and Statistics), the dataset covers about 97% of the formal labor market.

The unit of observation is employee associated to each employer. So an individual may appear more than once in the dataset. In this situation, they are treated as different cases. As all the information is as of December 31st, if there was any change over the year, only the last updated information is available. Also, it does not bring information regarding when variables suffered change and if variables suffered change more than once over the year. For this reason, this study focuses on job stayers, defined as the ones associated to the same employer with the same position as in the previous year. In this dataset, job stayers are identified by individual identification (PIS/Pasep), position (CBO) and employer identification (CNPJ/CEI).

Employers should inform base pay and the type of wage as in employment contract.[2] Since wages could be informed on daily, weekly, monthly or any other frequency - as long as it is what the employee contract says -, some standardization is required. The informed type of wage is not changed annually. Besides, when changed from one basis to another one, wage change will be out of the considered range, so it would be filtered. Thus, this variable would not cause issues by any means when calculating hourly wage change.

Table 1 shows a summarized look at RAIS. As displayed in the column (2), about 60% of employees are job stayers: this share of workers remain at the same firm as in the previous year, with the same job. The dataset was trimmed by removing cases with wage change greater than 50% or less than -50%. It reduces the number of observations by about 5%, as indicated in column (3) of Table 1. This procedure filters not only outliers, but it also avoids inaccurately informed cases.

Figure 1a shows percentiles of wage changes in 2007.[3] Wage changes sorted in ascending order look quite similar across years. It suggests that the proportion of each group - wage cut, wage freeze and wage increase - is almost constant. This is also observable by columns (4) and (5) of Table 1: the share of each wage change type is almost steady across the years. It is even more unequivocal when wage cut is observed: about 3.5% of job stayers experienced wage cuts, and this share ranges very little during the examined period. Only in 2015, there is a considerable increase: 4.5% of workers had wage cuts, corresponding to 1.9 million of employees - an increase of 0.5 million of cases, compared to 2014. However, there are less employees who had wage freeze, about 15% of job stayers, while in the previous years it remained at the level of 18%.

[2]According to the official RAIS guide, type of wage is understood as how wage is calculated, not the frequency of payment. For example, considering an individual who was hired for 20 hour-a-week job, with monthly wage of R$ 4000.00, paid weekly, his employer is required to inform that the wage is on monthly basis. However, this guide does not provide details concerning how the value of wage should be informed. Although most employers inform values on monthly basis, values on other bases could be found.

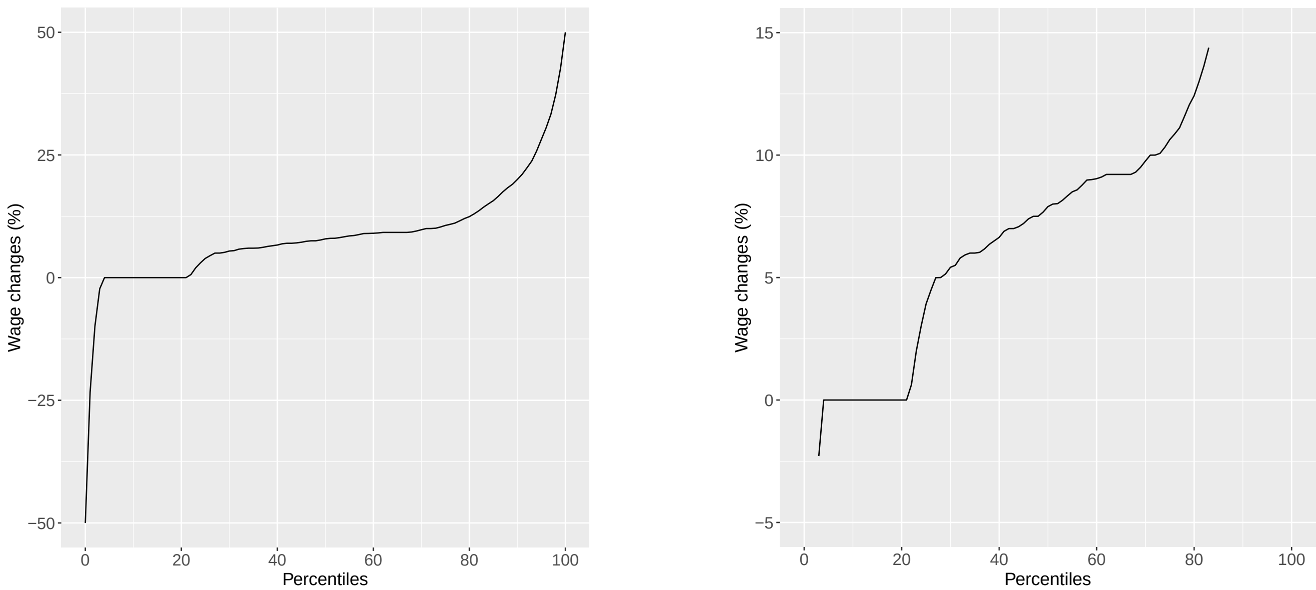
[3]Due to space limitations, similar figures for other years are omitted.

Table 1: Descriptive statistics - RAIS

	(1) Total	(2) Job stayers	(3) Trimming	(4) Wage freeze	(5) Wage cut	(6) Mean	(7) SD	(8) 1Q	(9) Median	(10) 3Q
2007-2008	54,649,133	31,882,955	29,588,261 (0.9280)	5,389,304 (0.1821)	1,029,908 (0.0348)	8.50	10.190	3.920	7.895	10.632
2008-2009	59,706,419	34,882,609	33,143,826 (0.9502)	6,283,993 (0.1896)	1,102,968 (0.0333)	8.00	9.646	3.012	7.000	11.805
2009-2010	61,126,896	36,938,363	35,120,895 (0.9508)	6,160,989 (0.1754)	1,125,585 (0.0320)	8.35	9.864	4.061	7.500	10.377
2010-2011	66,747,302	38,279,049	36,019,824 (0.9410)	6,223,547 (0.1728)	1,269,978 (0.0353)	9.38	10.605	5.074	8.795	12.222
2011-2012	70,971,125	41,891,960	39,871,838 (0.9518)	7,024,969 (0.1762)	1,241,730 (0.0311)	9.40	10.027	4.970	8.150	14.128
2012-2013	73,326,485	42,105,076	40,374,389 (0.9589)	6,902,283 (0.1710)	1,327,314 (0.0329)	8.41	9.621	5.000	8.325	10.069
2013-2014	75,400,510	44,719,068	43,030,354 (0.9643)	7,082,998 (0.1646)	1,381,239 (0.0321)	7.90	9.329	5.263	7.293	9.543
2014-2015	76,107,279	45,722,136	44,214,656 (0.9670)	8,534,949 (0.1930)	1,430,675 (0.0324)	7.74	8.729	2.920	8.468	10.000
2015-2016	72,175,102	44,579,138	42,986,317 (0.9643)	6,511,984 (0.1515)	1,935,961 (0.0450)	8.41	9.024	4.155	9.800	11.361
2016-2017	67,144,598	41,925,026	40,509,249 (0.9662)	7,644,310 (0.1887)	1,504,821 (0.0371)	5.19	8.114	1.730	5.000	7.000

This table shows basic information on job stayers of each year. A job stayer is defined as the employee who has the same job at the same employer as in previous base year. Column (1) refers to the total number of observations in RAIS of year t. Column (2) counts job stayers in each year. Column (3) shows how many job stayers are considered to the analysis - those with wage change ranging between -50% and 50%. Columns (4) and (5) count how many job stayers experienced wage freeze and wage cut, respectively. Columns (6) and (7) refer to mean and standard deviation of nominal wage changes for each group. Columns (8), (9) and (10) contain values of 1st, 2nd and 3rd quartiles of nominal wage changes.
Source: RAIS

Figure 1: Nominal wage changes in ascending order - 2007-2008



(a) RAIS 2007-2008 (b) Zoom in on NWC from -5% to 15%

This chart represents linear interpolation of wage changes observations in 2007-2008. Wage change is on y-axis and the percentile of wage change is on x-axis.
Source: RAIS 2007-2008

Still referring to Figure 1a, it hints about the likelihood of asymmetry of the distribution, mainly due to the amount of employees experiencing wage freeze. But it is not only this share of employees that contributes to the asymmetry. Comparing the lift in the interval between wage freeze and wage increase and wage changes from 5% to 10% , in Figure 1b, it is clear that wage changes are not uniform. Also, besides wage freeze, it seems that there is another focal point - about 9% of wage increase.

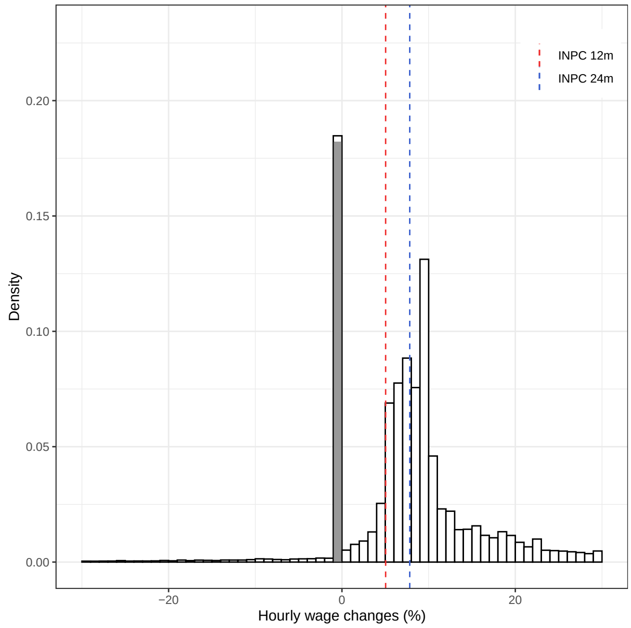
Indeed, in Figure 2, we can identify that a great number of employees had 9% - 10% of wage increase in 2007-2008. Moreover, the size of spike at 0 indicates not only that about 18% of employees had wage freeze, but also that there is no other bar - a certain percentage of wage change - that accumulates such a great number of employees.

Table 2 displays how each income group is defined. Table 3 shows descriptive statistics of RAIS per income group. Employees' wage in the base year is divided by minimum wage in force in the base year. As commented previously, the official guide does not specify whether the informed base wage should necessarily be in accordance to the type of wage or not. So it was necessary to adjust and filter some cases: 1) as the majority of cases are reported on monthly basis, hourly wage is calculated in order to check if it is greater than the hourly minimum wage[4]; 2) if it is less than the hourly minimum wage, then, assuming that the informed wage in on hourly basis, it is compared directly to the hourly minimum wage; 3) those cases that do not attend any of the 2 criteria above are filtered and removed from this data base.

Based on Table 3, in almost all years, lower groups are the ones whose wage increased the most, with the least variation among them. On the other side, the upper group is the one with the least wage increase but with the biggest divergence. It may be explained by the way how each group negotiates a raise: employees of lower groups have wage raise by collective bargaining and employees with higher income are more likely to ask for a raise individually rather than collectively. As the latter is more dependent on individual negotiation skills and its resulting raise applies to that specific employee, it is understandable that wage change of this group varies more.

[4]In most cases, about 90% of the dataset is on a monthly basis.

Figure 2: Histogram of hourly wage change - 2007-2008



The chart shows the wage changes of job stayers for the period of 2007-2008. On x-axis we have percentage changes in wage and on y-axis we have relative frequency of wage change. Each bar represents 1% of wage change, ranging from -30% to 30%. Gray part of the bar at 0 represents the number of employees who experienced wage freeze. Red dotted line indicates accumulated inflation rate during last 12 months - in this case, during 2007 - and blue dotted line refers to accumulated inflation during 24 months - from January 2007 to December 2008.
Source: RAIS 2007-2008

Table 2: Criteria applied to divide income groups - RAIS

Group	Wages measured in minimum wage
1	$1 < x \leq 2$
2	$2 < x \leq 4$
3	$4 < x \leq 10$
4	$10 < x \leq 20$
5	$x > 20$

Table 3: Descriptive statistics - RAIS per income group

	2007-2008	2008-2009	2009-2010	2010-2011	2011-2012	2012-2013	2013-2014	2014-2015	2015-2016	2016-2017
N_1	17,455,005	19,512,108	21,926,856	22,505,459	24,138,743	25,032,552	26,586,735	25,345,460	26,045,879	24,390,187
N_2	6,699,172	7,465,684	7,474,832	7,568,568	8,834,371	8,533,730	9,408,874	8,983,935	9,613,151	8,221,024
N_3	3,399,767	3,938,176	4,000,609	4,185,924	4,640,654	4,562,187	4,826,086	5,026,678	5,002,325	4,657,398
N_4	893,930	1,054,039	903,946	1,056,081	1,106,640	1,013,879	1,067,531	1,157,180	1,121,906	1,213,570
N_5	345,211	410,995	360,800	360,800	409,177	371,837	374,722	397,569	389,262	411,491
$Mean_1$	8.56	8.42	8.56	9.48	10.00	8.61	8.00	8.11	9.06	5.48
$Mean_2$	8.13	7.37	8.04	9.86	8.81	8.28	7.65	7.24	7.77	4.75
$Mean_3$	8.88	7.83	8.12	8.77	8.45	8.09	8.44	7.44	7.15	4.68
$Mean_4$	8.46	6.41	7.04	7.70	7.00	7.78	7.29	6.95	6.98	4.93
$Mean_5$	7.36	5.57	5.72	5.98	5.50	6.73	6.31	6.76	5.37	3.88
SD_1	9.03	8.61	8.69	8.52	8.94	8.45	8.21	7.68	7.62	6.74
SD_2	11.20	10.40	11.10	12.00	11.20	10.70	10.70	9.92	10.00	9.43
SD_3	11.80	11.50	11.90	13.00	11.60	12.00	11.30	10.50	11.80	10.45
SD_4	12.00	10.70	12.00	13.00	10.90	11.20	10.40	10.20	10.90	11.34
SD_5	12.80	11.00	11.90	12.40	10.70	9.93	10.30	10.50	10.40	11.90
$Median_1$	8.18	7.58	8.00	8.52	9.61	8.80	7.20	8.80	9.98	5.40
$Median_2$	7.15	6.43	7.00	8.91	7.54	8.00	7.50	8.17	9.14	4.30
$Median_3$	7.58	6.30	7.00	8.80	7.50	8.00	7.52	8.13	8.28	4.44
$Median_4$	7.67	6.01	6.50	8.25	6.98	7.60	7.00	7.68	8.00	4.86
$Median_5$	7.01	5.79	5.60	7.12	5.50	6.77	6.45	7.00	5.59	4.57
$Q1$-$Q3_1$	3.75-10.20	3.33-12.00	4.28-10.20	5.50-12.10	5.11-14.10	5.05-10.00	5.32-9.24	4.64-9.90	6.00-11.70	2.00-7.00
$Q1$-$Q3_2$	3.75-10.20	3.00-9.65	4.11-10.20	5.93-12.90	4.88-11.60	5.00-10.00	5.00-9.62	0.00-10.00	2.46-11.00	0.01-7.00
$Q1$-$Q3_3$	4.69-12.80	3.30-10.50	3.66-12.50	4.30-13.00	4.47-12.10	5.58-11.40	5.82-11.5	2.95-10.40	1.67-11.20	0.68-7.64
$Q1$-$Q3_4$	4.72-13.30	1.61-9.38	3.04-10.80	2.99-11.20	1.98 - 10.00	5.25-10.60	5.20-10.00	2.28-10.00	1.18-11.00	0.62-8.15
$Q1$-$Q3_5$	1.24-12.30	0.47-9.12	0.20-9.30	0.00-9.96	0.00-8.53	4.90-9.38	4.80-9.00	2.16-10.50	0.00-10.00	0.00-7.64

This table shows basic information on job stayers per each income group. N_i represents number of observations for each group. $Mean_i$, SD_i and $Median_i$ are respectively mean, standard deviation and median of nominal wage change for each group. $Q1 - Q3_i$ represents first and third quartiles of nominal wage changes, separated by income groups.
Source: RAIS

4 Methodology

In the case of nominal wage rigidity, as mentioned previously, the exact time when the wage changed is unknown. So the whole analysis on nominal wage rigidity is based on annual update, with an additional assumption that everyone who had wage change experienced it at the same time. Also, the trimmed RAIS is the only dataset used in this part. As seen in the previous section, labor market faces nominal wage rigidity, observable by the size of spike at 0. So, this study focuses on how to measure the extent of nominal wage rigidity.

The size of spike at 0 is a good starting point as a measure of wage rigidity. Actually, the reason why an employee experienced wage freeze is not observable: the wage could have been optimal at the time or the employer was not allowed to optimize by cutting or increasing wages. In theory, only the last case should be considered as wage rigidity, since the wage was optimized in the first case. However, in this case, the size of spike could be understood as the upper limit of nominal wage rigidity. This measure corresponds to the column (4) of Table 1.

As an attempt to decompose the wage rigidity into downward and upward rigidity, spike at 0 is broken down into 2 parts, weighted by wage increase and wage cut, as shown in expressions 1 and 2.

$$DNWR_t = \frac{WC_t}{WC_t + WI_t} \cdot WF_t \tag{1}$$

$$UNWR_t = \frac{WI_t}{WC_t + WI_t} \cdot WF_t \tag{2}$$

where WC_t is the share of wage cut in t, WI_t is the share of wage increase in t and WF_t is the share of wage freeze in t. Another measure for downward nominal wage rigidity is proposed by Dickens et al. (2007):

$$DNWR'_t = \frac{WF_t}{WF_t + WC_t} \tag{3}$$

This measure supposes that all the wage freezes are due to nominal downward rigidity. So, under the assumption of flexible wage setting, the employees who had wage freeze would have experienced wage cut.

Also, understanding the behavior of wage freeze over the years is an important task, especially in the context of staggered wage setting with random duration models. In this case, survival analysis on wage freeze is helpful to accomplish this task. Survival analysis requires that the event, survival and censoring to be defined to estimate survival probability. As wage change is not a traditional example of survival analysis, it is necessary to take a careful look at the population of interest.

Hereafter in t:

A) the event is defined as wage change in t;

B) the survival is a worker who had wage freeze in $t-1$ and remains at the same job, associated to the same employer in t;

C) employees are censored if they changed their job or/and they are not associated to the same employer in t.

If the event and censoring happened at the same time, the event is considered to have occurred before the censoring: this case is considered as not censored and counted as the event.

Once survival time is calculated and censored data is verified, the survival function is estimated using the Kaplan-Meier method, as in expression (4).

$$\hat{S}_t = \frac{WO_t - WC_t}{WO_t} \tag{4}$$

where WO_t is the total number of wage observations in t. Finally, fitting the exponential model to the data is the final exercise of this subsection. It offers an indirect estimation to the extent of nominal wage rigidity as in the staggered wage setting a la Calvo.[5] The generic survival regression in the following expression is estimated using Maximum Likelihood Estimation (MLE):

$$S_t = exp\{-\lambda_i \cdot t\} \tag{5}$$

where λ_i is a hazard function. When applied to all job stayers in Brazil for the whole studied period, then $\mathbf{x}\beta$ becomes a simple constant, λ. So expression 5 is rewritten as:

$$S_t = exp\{-\lambda t\} \tag{6}$$

Heterogeneity across regions is also analyzed by estimating:

$$\lambda_i = exp\{\beta_0 + \beta_1 x_{NE} + \beta_2 x_{SE} + \beta_3 x_S + \beta_4 x_{CO}\} \tag{7}$$

where β_0 is the constant and it measures the baseline risk - when the employee is from North in this case -, x_i with $i \in NE, SE, S, CO$ are the binary variables to identify the location associated to the job stayer, with NE being Northeast, SE being Southeast, S for South and CO for Middle West. In an analogous way, how wage stickiness is different across income groups is explored by estimating:

$$\lambda_i = exp\{\beta_0 + \beta_1 IG_2 + \beta_2 IG_3 + \beta_3 IG_4 + \beta_4 IG_5\} \tag{8}$$

where β_0 is the constant and it captures the wage stickiness of the lowest income group, IG_j with $j \in 2, 3, 4, 5$ are the binary variables to identify which income group an employee belongs to.

5 Results

This section is divided in two subsections. The first subsection refers to the extent of nominal wage rigidity, based on the concept of impossibility to increase or reduce wages. The second subsection presents the evaluation of nominal wage rigidity using the idea of wage stickiness.

5.1 How rigid are nominal wage?

Section 3 showed that there are signs of nominal wage rigidity in Brazil, noticeable by the the number of wage freeze. In this subsection, the results of the proposed measures in the previous section are shown. Hereafter, year refers to the base year, i.e, 2013 refers to 2013-2014, the period of 2008-2010 refers to 2008-2009, 2009-2010 and 2010-2011.

The analysis on nominal wage rigidity begins with comparing the size of spike at 0, shown in column (1) of Table 4. It counts how many employees experienced wage freeze from base year to the following year, expressed in relative term. Also, this number corresponds to the gray bar in Figures 3, 4. Except for 2014 and 2015, the observation of wage freeze is bigger than other nominal wage changes. These histograms make it clear that nominal wages are downward rigid, not only based on the size of spike at 0 NWR, but enhanced by the asymmetric form of the distribution as well. As shown in Table 4, this share of employees is quite stable over time, about 18%. Only in 2013-2015, this measure suffers noticeable oscillation: in 2013, it shrinks to 16.46%, then it rockets to 19.30% in 2014 and it plunges again to 15.15%; these two last numbers are the relative maximum and minimum during the studied period.

However, looking at this indicator requires extra attention, since it takes into account only the share of wage freeze. Back to Table 1, the difference in the total number of job stayers between 2014 and 2015 is smaller than the difference in the number of employees who experienced wage freeze between two years. So it is suggestive that the shrinkage in the number of employees with wage freeze is more

[5] Since exponential distribution may be considered as the continuous form of geometric distribution, we have the following relationship between these two distributions: $\lfloor X \rfloor \sim Y$, where $X \sim Exp(\lambda)$ and $Y \sim Geom(p)$, with $p = 1 - exp\{-\lambda\}$.

Table 4: Nominal wage rigidity measures

	(1)	(2)		(3)
		DNWR	UNWR	DNWR2
2007	18.21%	0.78%	17.44%	83.96%
2008	18.96%	0.78%	18.18%	85.07%
2009	17.54%	0.68%	16,86%	84.55%
2010	17.28%	0.74%	16,54%	83.05%
2011	17.67%	0.67%	17,00%	84.98%
2012	17.10%	0.68%	16.42%	83.87%
2013	16.46%	0.63%	15.83%	83.68%
2014	19.30%	0.77%	18.53%	85.64%
2015	15.15%	0.80%	14.35%	77.08%
2016	18.87%	0.86%	18.01%	83.55%
All years	17.61%	0.74%	16.87%	83.54$

This table shows nominal wage rigidity measures for each year. Column (1) refers to the size of zero nominal wage. Column (2) is divided into 2 parts: DNWR refers to the downward nominal wage rigidity and UNWR refers to the upward nominal wage rigidity, calculated based on expressions (2) and (3). Column (3) refers to the downward nominal wage rigidity, proposed by Dickens et al (2007).
Source: RAIS

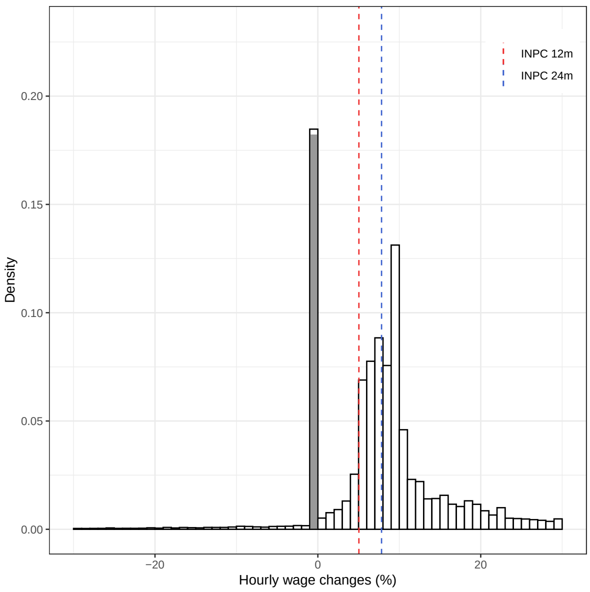
strongly associated to lower employment and less job stayers than more employees with wage cut in this year. Also, the decline in this measure is not necessarily related to more flexible wage setting, but it may just reflect changes in absolute numbers of wage cut and wage freeze. When considered a longer period, for example, the whole studied period, it gives a straightforward answer regarding the existence of nominal wage rigidity: annually at least 15% of job stayers experience nominal wage freeze and the stability in this number over time is a strong evidence of the existence of a barrier to flexible wage adjustment; especially, it shows that workers are strongly resistant to nominal wage cut.

Column (2) in Table 4 refers to the decomposition of the share of wage freeze into two parts, weighted by the share of wage increase and wage cut. This measure is based on the assumption that wages are both downward and upward rigid. As the optimal wage is not observable, an extra assumption is required: the share of wage freeze that is proportional to the wage increase is attributed to upward NWR (UNWR) and another share corresponding to the weight of wage cut is assigned to downward NWR (DNWR).

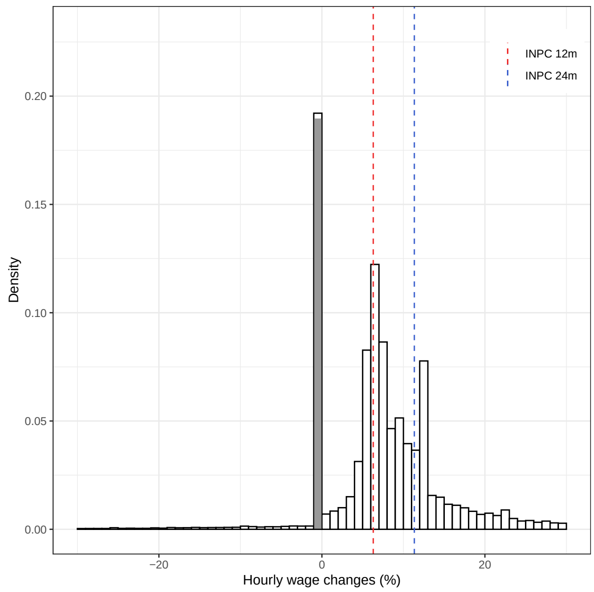
As the share of employees with wage cut is very low in the Brazilian formal labor market over time, about 3.5% over the studied period, this measure points to UNWR as the main reason for wage freeze. Based on this measure, the problem of not having wage increase is more present than the problem of not having wage cut. As this measure uses all components of the population - wage cut, wage freeze and wage increase -, it is more sensitive to fluctuations in the shares of each component, instead of changes in the absolute numbers. As seen in Table 1, between 2007 and 2008, the number of employees who experienced wage freeze increases by 0.9 million, corresponding to an yearly variation of 16.5%, but it does not affect this indicator since the proportion of the components remains unchanged. In 2015, this measure increases slightly, despite the decline in the number of employees experiencing wage freeze.

Column (3) refers to the DNWR measure in expression (3). It supposes that all the employees who had wage freeze would have wage cut under flexible wage setting, implying that DNWR is the only responsible for wage freeze. As wage cut is still much smaller compared to wage freeze, this measure indicates that DNWR in the Brazilian labor market is very high, varying between 77% to 85%. It may not seem to be pertinent to the reality if only the absolute numbers are analyzed, but evaluating the oscillation in the indicator offers an overview on the behaviour of NWR over time. In fact, as the share of employees who experienced wage cut is very small and the number of observations of wage freeze does not change across years, this indicator ends up being quite stable over time as well. Only in 2015,

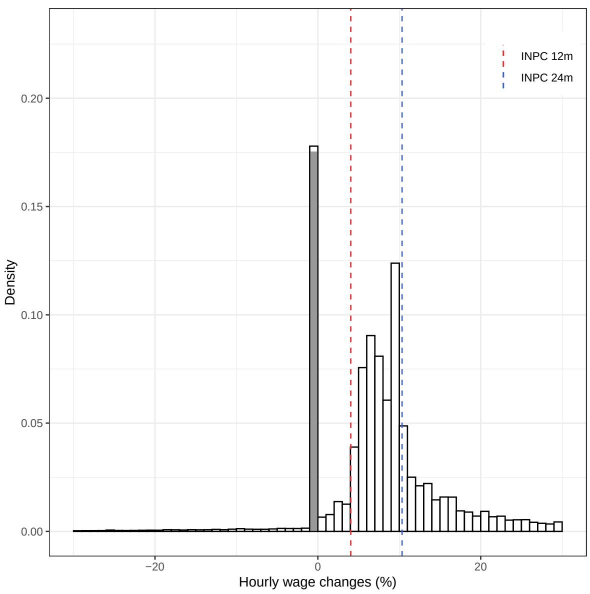
Figure 3: Histogram - Nominal wage changes (1)



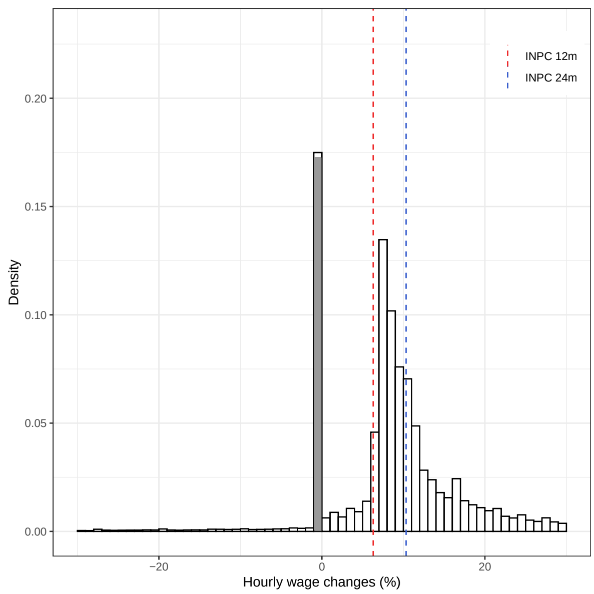
(a) 2007



(b) 2008



(c) 2009



(d) 2010

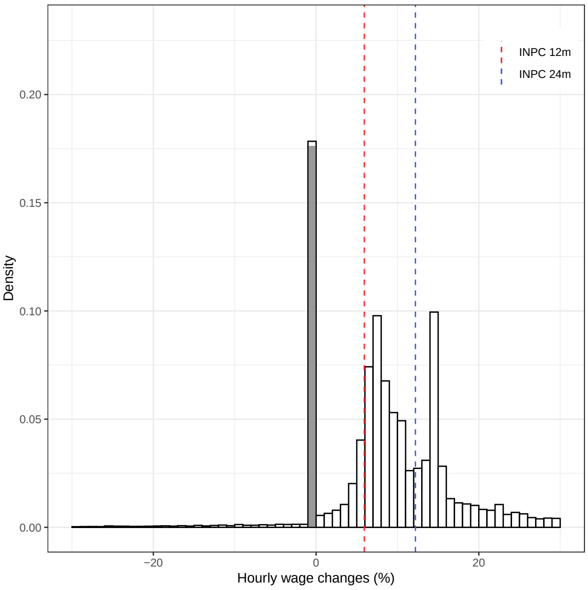
a sudden plunge is observed due to the decline in the share of wage freeze. Since the total number of employed workers declined in this year, it is likely that they were less resistant to wage cut in order to keep their jobs, resulting in reduced NWR.

Three different simple indicators are shown here. As they use different assumptions, the divergence in results is seen both in the absolute numbers and in the behavior over time. Each one can be useful in different situations. Indicator (1) gives us the most intuitive answer when asked about the extent of NWR. Indicator (2) is sensitive to variation in the 3 components - wage freeze, increase and cut. Indicator (3) is useful when the economy is under turbulence, so all agents face the trade-off between wage cut and keeping jobs.

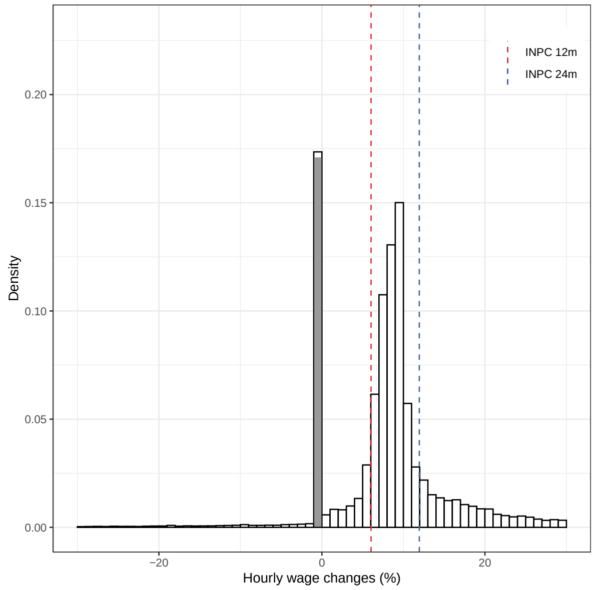
5.2 Is nominal wage sticky?

The indicators shown in the previous subsection show how wage behaves in each year, but they do not provide information regarding the behaviour over time. When the idea of duration is embraced in a model, then information on how long it takes to have wage change is required. So survival analysis on

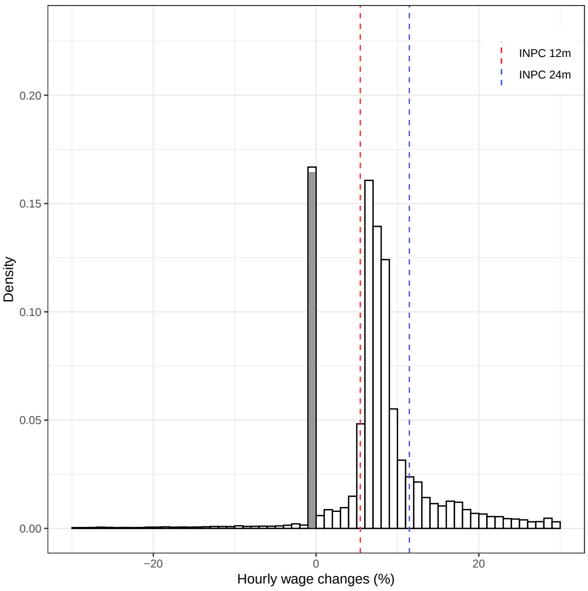
Figure 4: Histogram - Nominal wage changes (2)



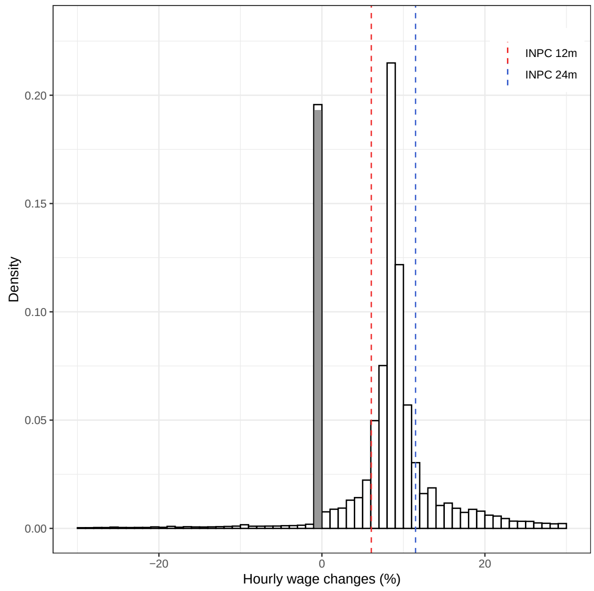
(a) 2011



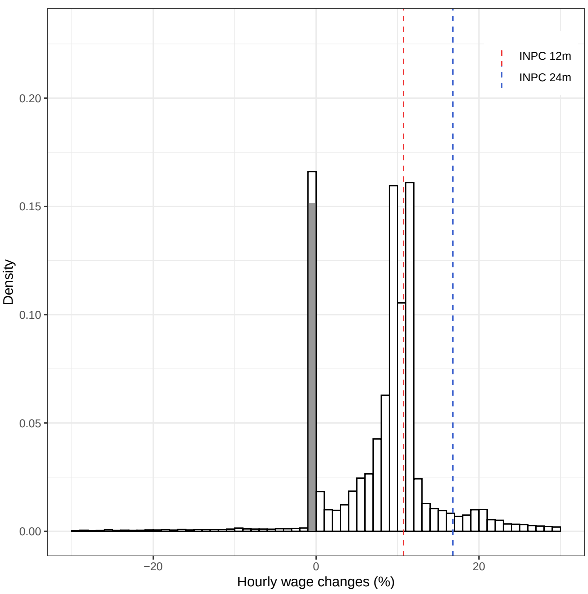
(b) 2012



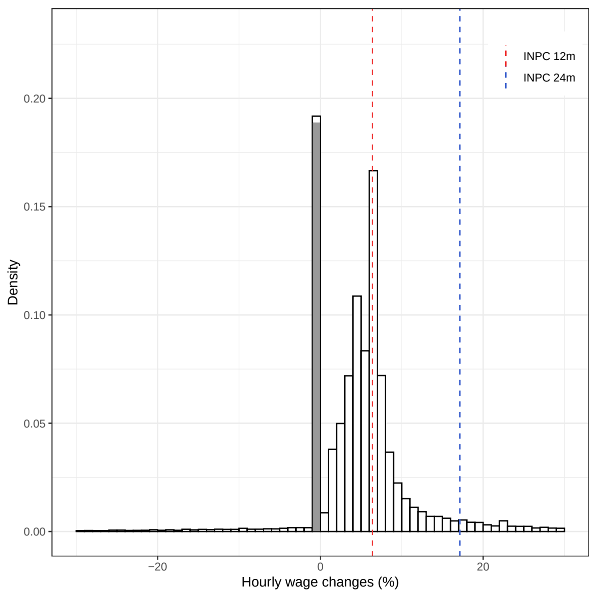
(c) 2013



(d) 2014



(e) 2015



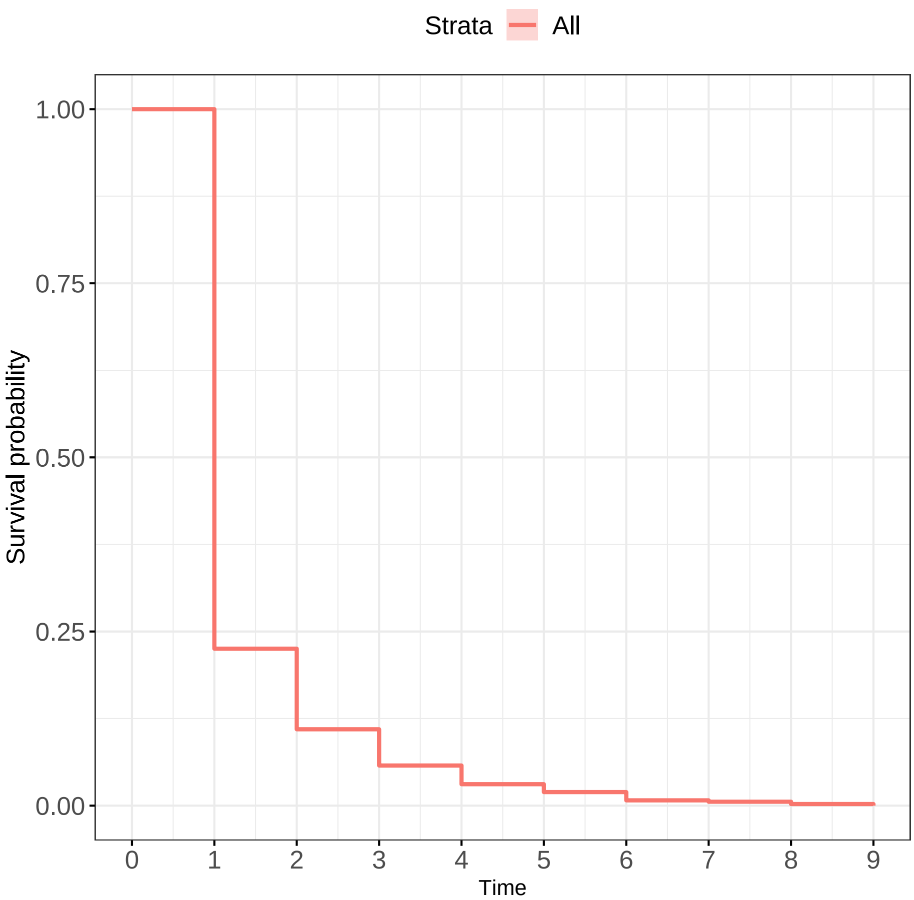
(f) 2016

The chart shows the wage changes of job stayers for each year. All the variables are the same as in figure 2.
Source: RAIS

wage freeze is conducted in order to assess wage stickiness.

Figure 5 illustrates the KM survival curve of wage freeze for job stayers during the studied period in Brazil. Table 5 shows corresponding survival probabilities. As seen in the table, the probability of not having wage changed by the end of the second year is 0.23. And about 11% of job stayers are expected to have wage freeze for 3 years. Observing the number of censored cases, 15% to 20% of job stayers of the previous year are expected to quit or change jobs by the end of the year in the first 4 years.

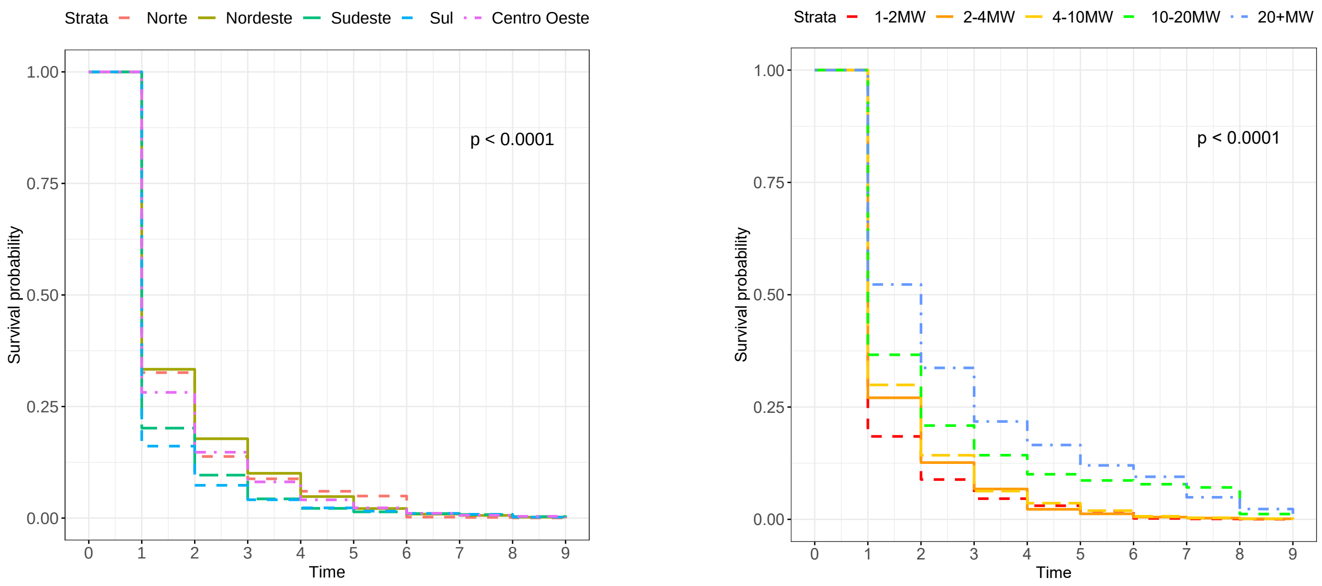
Figure 5: KM estimation for wage freeze



This chart shows estimation for job stayers' survival probability of wage freeze using KM estimator. Time is on x-axis and the survival probability is on y-axis.
Source: RAIS, original creation

Now, the same analysis is performed with division per region to check if there is heterogeneity in wage stickiness towards geographic location. Figure 6a and Table 6 are suggestive of some heterogeneity, corroborated by a log rank test result with *p-value* lower than 0.0001. Specifically, employees from North and Northeast have the stickiest wage, while South and Southeast are the regions with the least sticky wages. Also, observing the number of censored cases brings interesting information here. The difference in the share of employees who changed job or employer - censored employees - may reflect the difficulty in finding jobs for workers or in replacing the workforce for employers. For example, in North, where the labor pool is considered limited compared to other regions, the share of censored employees is smaller than in Northeast, suggesting that searching new employees and new jobs is relatively more difficult in North. Meanwhile, in Northeast, when employers faced wage increase and workforce replacement, the number of censored hints that employers are more inclined to replace workers and it is less difficult to

Figure 6: KM estimation for wage freeze - subgroups



(a) By region

(b) By income group

This chart shows estimation for job stayers' survival probability of wage freeze using KM estimator for each subgroup. The panel on the left shows estimation for each region and the panel on the right shows estimation for each income group. Time is on x-axis and the survival probability is on y-axis
Source: RAIS, original creation

find new jobs as well, compared to workers in North. Workers from South and Southeast, meanwhile, are the most resistant to wage freeze: 16% and 20% of job stayers have wage frozen in the first 2 years, respectively, while in other regions this rate is from 28% to 34%. Also, these are the regions with the highest ratio between the number of wage changers and the number of job switchers. It indicates that here both employers and workers prefer not to change their employment relationship with each other, instead of hiring new workers or searching for new jobs.

Table 5: Estimation of survival function for job stayers - all years

Time	N.risk	N.event	N.censor	S(t)	SD
1	$48,762,885$	$37,774,275$	$7,929,048$	0.225	0.0003
2	$3,059,562$	$1,571,450$	$667,740$	0.110	0.001
3	$820,372$	$389,150$	$128,665$	0.058	0.001
4	$302,557$	$141,054$	$36,553$	0.031	0.002
5	$124,950$	$46,029$	$9,463$	0.019	0.003
6	$69,458$	$42,430$	$4,203$	0.008	0.006
7	$22,825$	$5,877$	$12,420$	0.006	0.007
8	$4,528$	$2,711$	209	0.002	0.019
9	$1,608$	$1,608$	0	0.000	-

This table shows estimated survival function for job stayers. Second column refers to the number of employees in the beginning of each year, third column refers to the number of wage change during the year. Fourth column refers to the number of censored cases. SD refers to standard deviation of estimation, S(t).

Whether there is any difference across income groups is a relevant question as well. Shown in Table 7 and Figure 6b, there is a clear positive association between income and the persistence of 0 wage change. The higher is the wage, the less rigid is the employee regarding base wage change. As a low income earner is the main target of collective bargaining, his wage depends more on the result of CBA than his direct and individual negotiation with the employer. On the other hand, a high income earner is more likely to have an individual wage negotiation, also it is unlikely that he has an "automatic" mechanism for wage raise, as low income workers. High income employees are more likely to have alternative and non-regular and effort-related earnings besides the base salary, while low income earners' main income source is very likely to be the base salary. In this way, the former group might be more interested in having increase in effort-related earnings, rather than in base salary, while the latter group's focus is on base wage raise. Now, comparing the number of those who changed job or employer and the number of those who had wage change at the same employer, the higher income is also associated to higher turnover (per job). Wage increase is certainly a positive factor for all groups to keep the employment relationship, nonetheless this impact is less strong on higher income groups, compared to lower income employees.

As the final result of the survival analysis, exponential distribution is fitted to the dataset using Maximum Likelihood Estimation (MLE), shown in Table 8. The estimated values refer to the hazard functions. Model (1) refers to all job stayers of all studied years in Brazil, as described in expression (5). As there is no distinction, all job stayers have the common probability of having wage freeze. Using the relationship between Exponential distribution and Geometric distribution, we have $\hat{p} = 1 - exp\{-0.291\} \approx 0.252$. It leads to the estimation of nominal wage rigidity in random duration setting a la Calvo: the probability of a job stayer to have wage freeze in each period is about 25.2%. Consequently, it is expected that an employee has no wage change for about 1.3 years. Model (2) refers to the exponential regression described in expression (7), including dummy variables for regions. As the baseline risk refers to North, the coefficients shown in the table are read as hazard ratio. Wages of job stayers from North and Northeast are expected to be more rigid, while South and Southeast are the most flexible in Brazil. The estimation is significant at the level of 1%; also, the heterogeneity across regions is significant at this level as well. Model (3) is equivalent to the regression in expression (8). The baseline group is IG_1, the lowest income earners. As seen in Table 7, the wage of this group is expected to be the least sticky, while IG_5 is expected to have the stickiest wage. Estimated coefficients are significant at 1% and the wage stickiness of income groups is statistically different at 1%.

6 Conclusions

This study investigates the existence and the extent of nominal wage rigidities for job stayers in Brazil. Divided in 2 questions related to wage rigidities, RAIS dataset, Brazilian administrative records on each employer's staff, reported by firms, is explored. The first discussion is on the extent of nominal wage rigidity, estimated using the observation of wage freeze and wage cut. Three different approaches are used to assess the nominal wage rigidity. As the NWR measures have different assumptions, it produces disparate results. However, the shares of employees experiencing wage freeze and wage cut are quite stable over the examined years.

The second question is on the stickiness of nominal wage. Using KM estimation method, survival function for the job stayers is estimated. Two main findings are reported. First, about 73% of job stayers have wage changed after two years; however, the persistence of wage freeze is also high. Second, about 6% of job stayers are expected to experience wage freeze for 4 consecutive years. Besides, about 15% of job stayers of the previous year are expected to quit or change jobs by the end of the year. Segregated by regions and income groups, the same analysis is repeated to verify the existence of heterogeneity across these variables. North and Northeast are the regions with the stickiest nominal wages, while employees in South experience the least wage staggering. Also, income level is positively associated to the extent of wage stickiness. All these results are corroborated by the survival regression, significant at 1%. Also, using the relationship between Geometric distribution and Exponential distribution, Calvo probability is estimated.

References

AVOUYI-DOVI, S., FOUGERE, D. GAUTIER, E. Wage rigidity, collective bargaining and the minimum wage: evidence from French agreement data. *The Review of Economics and Statistics*, VOl. 95. 2013

BABECKY, J.; DU CAJU, P.; KOSMA, T.; LAWLESS, M.; MESSIAN, J.; ROOM, T. Downward Nominal and Real Wage Rigidity: Survey Evidence from European Firms. Working Paper Research 182, National Bank of Belgium. 2009

BAUER, T.K.; BONIN, H.; SUNDE, U. Real and Nominal Wage Rigidities and the Rate of Inflation: Evidence from German Micro Data. IZA Discussion Paper No.959. 2004

BEWLEY, T. Fairness, Reciprocity, and Wage Rigidity. IZA Discussion Papers No. 1137. 2004

BLANCHARD, O.; GALI, J. Real wage rigidities and the New Keynesian Model. *Journal of Money, Credit and Banking*. Vol. 39. 2007

CALVO, G. Staggered prices in a utility-maximizing framework. *Journal of Monetary Economics*. Vol. 12. 1983

CARVALHO, F.A., VALLI, M. Fiscal Policy in Brazil through the Lens of an Estimated DSGE Model. Working Papers Series 240, Central Bank of Brazil, Research Department. 2011

DEELEN, A.; BERNEEK, W. Measuring downward nominal and real wage rigidity - why methods matter. CPB Discussion Paper 315. CPB Netherlands Bureau for Economic Policy Analysis. 2015

DICKENS, W.T.; GOETTE, L.; GROSHEN, E. L.; HOLDEN, S.; MESSIAN, J.; SCHWEITZER, M.E.; TURUNEN, J.; WARD, M.E. How wages change: micro evidence from the International Wage Flexibility Project. *Journal of Economic Perspectives*. Vol. 21. 2007

DU CAJU, P.; KOSMA, T.; LAWLESS, M.; MESSIAN, J.; ROOM, T. Why Firms Avoid Cutting Wages: Survey Evidence from European Firms. Policy Research Working Paper;No. 6976. World Bank Group. 2014

ELSBY, M. W. Evaluating the economic significance of downward nominal wage rigidity. *Journal of Monetary Economics*. Volume 56. 2009

ELSBY, M. W.; SOLON, G. How prevalent is downward rigidity in nominal wages? International evidence from payroll records and payroll slips. *Journal of Economic Perspectives*. Vol. 33. 2019

FALLICK, B.; LETTAU, M.; WASCHER, W. Downward nominal wage rigidity in the United States during and after the Great Recession. Working papers 16-02R, Federal Reserve Bank of Cleveland. 2016

GOETTE, L.; SUNDE, U.; BAUER, T. Wage rigidity; measurement, causes and consequences. *The Economic Journal*. Vol. 117. 2007

MAZALI, A. A.; DIVINO, J. A. Real wage rigidity and the new Phillips curve: the Brazilian case. *Revista Brasileira de Economia*. Vol. 64. 2010

MCLAUGHLIN, K.J. Rigid wages? *Journal of Monetary economics*. Vol. 34. 1994

MESSIAN, J. SANZ-DE-GALDEANO, A. Wage rigidity and disinflation in emerging countries. *American Economic Journal: Macroeconomics*. Vol. 6. 2014

PORTUGAL, P. Wage setting in the Portuguese labor market: a microeconomic approach. Economic Bulletin and Financial Stability Report Articles and Banco de Portugal Economic Studies, Banco de Portugal, Economics and Research Department. 2006

SCHUMANSKI, E.L. Asymmetric price and wage rigidity in Brazil: estimation of a DSGE model via particle filter. XI Seminar on Risk, Financial Stability and Banking of the Banco Central do Brasil. 2015

VASCONCELOS, B.F.B., DIVINO, J.A. O desempenho recente da pol ıtica monet aria brasileira sob a otica da modelagem DSGE. Working Papers Series 291, Central Bank of Brazil, Research Department. 2012

Table 6: Survival analysis - per region - 2008-2016

Region	Time	N.risk	N.event	N.censor	S(t)	SD
North	1	2,657,236	1,788,879	484,159	0.327	0.001
	2	384,198	222,666	50,005	0.137	0.002
	3	111,527	41,215	14,778	0.087	0.003
	4	55,534	17,737	4,040	0.059	0.004
	5	33,757	6,099	1,463	0.048	0.005
	6	26,195	25,054	496	0.002	0.029
	7	645	213	263	0.001	0.040
	8	169	124	6	0.0004	0.134
	9	39	39	0	0.000	-
Northeast	1	6,664,881	4,402,957	1,504,733	0.339	0.001
	2	757,191	355,848	155,321	0.180	0.001
	3	246,022	111,127	33,439	0.099	0.002
	4	101,456	52,622	10,832	0.047	0.004
	5	38,002	20,620	2,828	0.022	0.007
	6	14,554	8,327	1,146	0.009	0.012
	7	5,081	1,838	1,919	0.006	0.016
	8	1,324	851	92	0.002	0.040
	9	381	381	0	0.000	-
Southeast	1	27,503,635	21,856,278	4,224,822	0.205	0.0004
	2	1,422,535	738,440	328,838	0.099	0.001
	3	355,257	193,770	50,586	0.045	0.002
	4	110,901	54,492	12,096	0.023	0.004
	5	44,313	18,977	3,383	0.013	0.005
	6	21,953	6,230	1,840	0.009	0.007
	7	13,883	3,355	7,651	0.007	0.008
	8	2,877	1,732	94	0.003	0.024
	9	1,051	1,051	0	0.000	-
South	1	8,626,752	7,227,127	1,064,899	0.162	0.001
	2	334,726	183,128	80,321	0.073	0.002
	3	71,277	31,538	15,711	0.041	0.004
	4	24,028	10,674	3,507	0.023	0.007
	5	9,847	3,202	1,517	0.015	0.010
	6	5,128	1,660	655	0.010	0.014
	7	2,813	585	1,775	0.008	0.017
	8	453	342	11	0.002	0.084
	9	100	100	0	0.000	-
Middle West	1	4,256,587	3,053,919	835,604	0.283	0.001
	2	367,064	174,962	82,495	0.148	0.002
	3	109,607	49,630	18,003	0.081	0.003
	4	41,974	21,575	8,186	0.039	0.006
	5	12,213	5,380	946	0.022	0.010
	6	5,887	3,165	496	0.010	0.017
	7	2,226	897	846	0.006	0.025
	8	483	202	9	0.004	0.046
	9	272	272	0	0.000	-

Table 7: Survival analysis - per income group - 2008-2016

IG	Time	N.risk	N.event	N.censor	S(t)	SD
1	1	30,354,809	24,749,583	4,331,189	0.185	0.0004
	2	1,274,037	662,047	293,888	0.089	0.001
	3	318,102	152,800	62,447	0.046	0.002
	4	102,855	35,099	12,585	0.030	0.003
	5	55,171	21,252	2,693	0.019	0.005
	6	31,226	27,522	894	0.002	0.016
	7	2,810	1,373	300	0.001	0.024
	8	1,137	709	40	0.0004	0.045
	9	388	388	0	0.000	-
2	1	10,604,686	7,734,645	1,926,638	0.271	0.001
	2	943,403	502,658	175,076	0.126	0.001
	3	265,669	123,684	31,133	0.068	0.002
	4	110,852	74,113	9,485	0.022	0.005
	5	27,254	12,230	2,554	0.012	0.007
	6	12,470	7,383	1,052	0.005	0.013
	7	4,035	1,751	491	0.003	0.019
	8	1,793	1,021	59	0.001	0.033
	9	713	713	0	0.000	-
3	1	6,143,522	4,304,645	1,268,911	0.299	0.001
	2	569,966	298,279	119,544	0.143	0.002
	3	152,143	85,005	21,362	0.063	0.003
	4	45,776	19,553	6,868	0.036	0.005
	5	19,355	8,909	1,459	0.019	0.008
	6	8,987	5,803	507	0.007	0.017
	7	2,677	1,336	200	0.003	0.025
	8	1,141	619	84	0.002	0.041
	9	438	438	0	0.000	-
4	1	1,236,175	783,218	295,550	0.366	0.001
	2	157,407	67,725	31,122	0.209	0.002
	3	58,560	18,499	5,877	0.143	0.004
	4	34,184	10,154	4,262	0.100	0.005
	5	19,768	2,705	1,080	0.087	0.006
	6	15,983	1,555	1,642	0.078	0.006
	7	12,786	1,168	11,223	0.071	0.007
	8	395	329	8	0.012	0.113
	9	58	58	0	0.000	-
5	1	423,693	202,184	106,760	0.523	0.001
	2	114,749	40,741	48,110	0.337	0.003
	3	25,898	9,162	7,846	0.218	0.005
	4	8,890	2,135	3,353	0.166	0.008
	5	3,402	933	1,677	0.120	0.013
	6	792	167	108	0.095	0.023
	7	517	249	206	0.049	0.048
	8	62	33	18	0.023	0.144
	9	11	11	0	0.000	-

Source: RAIS

Table 8: Fitting exponential distribution - Brazil - 2008-2016

		Dependent variable:			
		$S(t)$			
		Coefficient	Std. Error	χ^2	DF
(1)	$Constant$	0.291^{***}	0.000157	-	-
(2)	$Constant$	0.442^{***}	0.000690	$313,837.3^{***}$	4
	$Northeast$	0.016^{***}	0.000823		
	$Southeast$	-0.188^{***}	0.000721		
	$South$	-0.245^{***}	0.000781		
	$Middle - West$	-0.071^{***}	0.000882		
(3)	$Constant$	0.226^{***}	0.000197	$326,411.6^{***}$	4
	IG_2	0.122^{***}	0.000397		
	IG_3	0.160^{***}	0.000501		
	IG_4	-0.245^{***}	0.000781		
	IG_5	-0.071^{***}	0.000882		

*p<0.1; **p<0.05; ***p<0.01